FUZZY DETECTION SYSTEM FOR EFFICIENT PEDESTRIAN DETECTION IN TRAFFIC AREAS

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ABSTRACT

Fuzzy inference is a very important aspect of computer science with numerous applications in expert system and computer vision. This paper has developed fuzzy inference models to reveal traffic conditions and behavior in public road locations. This approach employs some fuzzy logic systems with knowledge-based analysis to define useful linguistic variables and appropriate membership functions for mapping the input parameters to reduce the problem of high traffic congestion. Traffic Pedestrian movement and density have been used as input data to construct models while defuzzification process represents the output, which can be used at pedestrian detection levels with various range in membership values. The traffic movement, density and pedestrian level detection have been used to determine the congestion level or traffic condition of different locations considered in this paper. The results achieved have shown that the calculated traffic density and movement traffic level could be used to control the traffic movement and pedestrian levels. The closer the value of congestion level to 1, the higher the traffic level, however, when congestion level moves closer to zero the traffic level decreases. The experimental results demonstrated that fuzzy inference models could be effectively used for pedestrian detection in transportation systems.

Keywords— Fuzzy Detection, Inference, Pedestrian, Traffic and Defuzzification

INTRODUCTION

Fuzzy logic is an effective way to address the problem of imprecisions or errors in the inputs of a knowledge base in order to arrive at precise values for outputs. It can be employed to capture the broad categories model that will reflect the relationship between input and output variables in the data set. Therefore, clustering is a very important method to generate grouping within a very big data set, and could be used to accurately demonstrate the relationships in the data (Gosaina and Dahiya,2016; Raj,2019). This approach could be used to group pedestrians' features and effectively applied to build Fuzzy logic systems for accurate detection and classification of moving objects (Zhang et al., 2017). The most current approach, which uses per-window method is flawed and can sometimes fail to predict the actual performance in pedestrian detections (Robert et al., 1986; Pavithra et al., 2018). To the best of our knowledge, no researcher has ever applied fuzzy logic to address the problems of pedestrian detection in traffic areas. This is very interesting because most of the existing algorithms in Fuzzy logic have one problem or the other in this research area (Mamdani and Assilian ,1975; Muthukumar,2015; Navarro,2017; Kalinic et al., 2019), making the computational accuracy to be very difficult and access to real life data could be a very serious challenge. How can we determine the appropriate membership function for the pedestrian features using the fuzzy logic? What is the ability of the generated Fuzzy inference system in terms of detecting the moving objects? Can fuzzy rules be effectively applied for computing a robust model? How can we determine the performances of the model in terms of recognition accuracy and other important parameters? Answers to these research questions could be very useful in developing a system to detect any moving objects in traffic areas. If-then statement is the most common method in fuzzy logic to join an input space with an output space to formulate rules. However, ordering of rules is not important but many rules can be generated concurrently. These can be the primary mechanism for accomplishing our goals in this research since they represent variables and adjectives for obtaining detection models. Though, few researchers have worked in this area but the proposed work using newly constructed models should be able to outperform the existing systems in terms of space and time complexities, and the overall computational efficiency. This research work therefore aims to identify the key elements of fuzzy pedestrians in traffic areas and applies these components to develop robust models for improving accurate recognition.

METHOD FOR COMPUTING FUZZY INFERENCE SYSTEM

The theory of fuzzy logic could be measured by human thinking, which represents the occurrence of uncertainty in reasoning but a logic with truths, connectivity and inferences are traditional way of manipulating uncertain concepts in developing inference system (Yadav et al., 2015; Ton-That et al., 2016; Liu et al., 2018). This can be illustrated by stating Y as a non-empty set such that fuzzy set B in Y is characterized by its membership function: $\mu B:Y \rightarrow [0, 1]$ while $\mu B(y)$ can be referred to as the degree of membership with element y in set B for each $y \in Y$. The level at which 'y is B' is true can be represented as y in B. The process of transforming inputs with ordinary numbers into fuzzy sets, is called fuzzification Module while defuzzification converts fuzzy set generated by knowledge base into ordinary values. The knowledge base for fuzzy logic system contains IF-THEN commands to process the fuzzy sets. The inference system could be used to process human reasoning by taking decision on fuzzy input sets from fuzzification module combined with IF-THEN rules from the knowledge base to process the fuzzy output set (Figure 1).

The term that can be used to determine if an element belong or not belong to a particular set and with which degree of membership do they belong is called membership function. This can be achieved by assigning each element of the input variable with a membership value between 0 and 1. Five different measures that could be generally used to represent a membership function are: Gaussian, bell, sigmoidal, trapezoidal and triangular. The implementation of input variables and membership function values could be used to generate models for solving problems in computer vision.

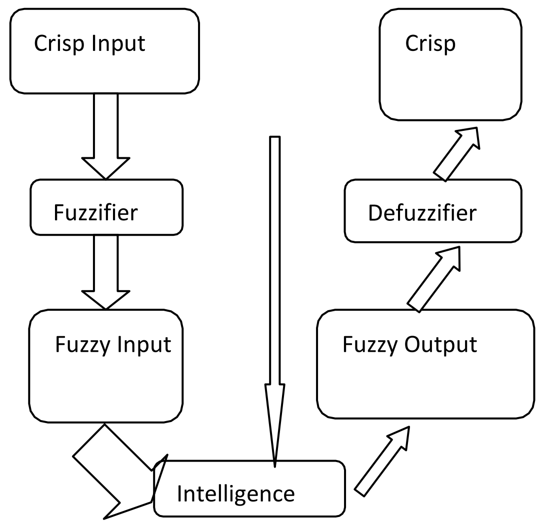

Figure 1: Implementation of fuzzy logic system on fuzzy sets of variables

Fuzzy inference engine has the ability to effectively use the information from the knowledge base and that of input variables to generate excellent results. The process itself involves several phases as we have previously discussed. The fuzzy logic system has four major parts as presented in Figure 1, the fuzzification module, which converts the inputs of ordinary numbers to fuzzy sets by dividing input signal into five different steps is the first step in this process. In this research, the two input variables that would be implemented for developing a fuzzy inference model are the pedestrian movement and density while the output parameter is pedestrian level (pl). The term movement represents the total number of vehicles through the city within a certain period of time; the data set has five lanes. Density denotes pedestrians moving through certain location in terms of longitude and latitude on the highways within that direction in every 60 seconds. How do we now calculate the density? The traffic density can be calculated using datasets to measure the number of pedestrians crossing the highways in a certain period. Let's assume vehicles are of equal length, the relationship between relative occupancy (V) and density (D) can be calculated as follows:

$$V = L*D \tag{1}$$

Where L is the length of vehicles across the highways in those locations of concern. The two input variables and one output would be fuzzified to generate many membership functions. The functions would allow one to measure linguistic terms and determine a fuzzy set diagrammatically. Every element of X is joined to a value between 0 and 1. The intensity of membership in X is quantified with set A. X-axis denotes the universe of discourse, while y-axis denotes level of membership within the interval of 0 and 1. In this research, the traffic density can be divided into five parameters such as: Very Low Density (VLD), Low Density (LD), Medium Density (MD), High Density (HD), and Very High Density (VHD). For the pedestrian movement input variable, this can be divided into Free Movement, Reasonably Free Movement, Stable Movement, Unstable Movement, Near-congestion Movement and Congested Movement. There can be numerous functions to fuzzify these input variables but the membership functions to fuzzify the traffic density are shown in Figure 2.

In knowledge base, it is important to establish a system, which indicates how to project input variables onto output space. It can be achieved by applying if-then fuzzy commands in the form of:

$$\textit{If } k \textit{ is } A, \textit{ Then } m \textit{ is } B \tag{2}$$

Where k represents input variable and m represents output variable, where A and B are values that enable if-then conditional statement to work with human decisions. The most common operators that can be used to combine these membership values are AND and OR operators. These operators apply function max and min to join membership values together to obtain fuzzy values.

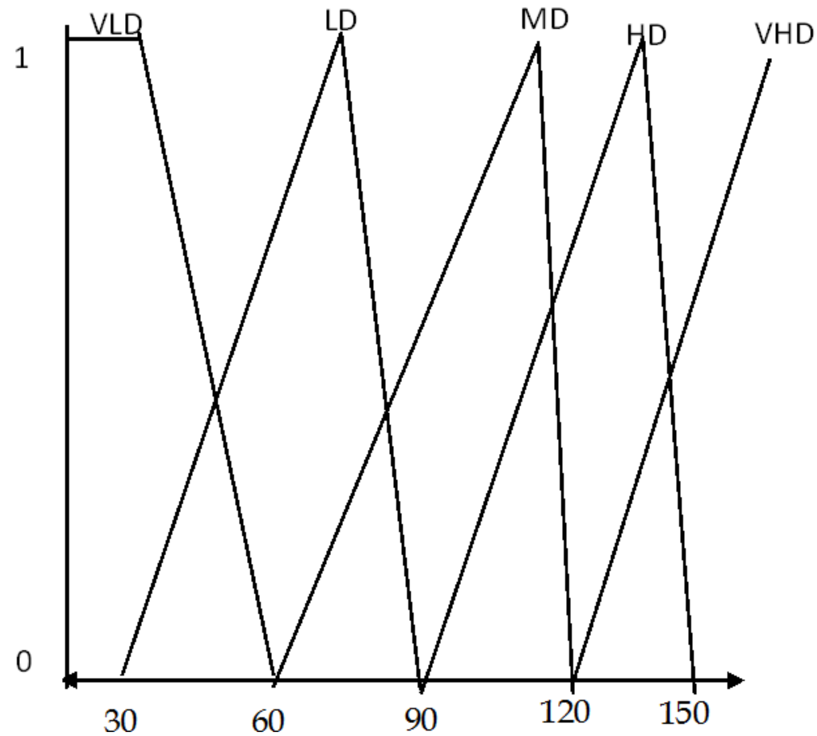

Figure 2: Triangular membership function for traffic density

Some variables that are required to build a detection system must be properly defined in simple words and applied appropriately. In this research work, pedestrian movement and density are some of the input parameters defined to develop models in detecting pedestrian across the highways.

In Figure 3, the membership functions of pedestrian level were constructed to determine the variations in the input pedestrian level, these membership values always vary between 0 and 1. The knowledge base commands were then created using defined variables; this can be in the form of a matrix such that some set of rules would be built into the knowledge base using IF-THEN-RULES structure. This structure is generally used to combine different rules in order to extract useful decision. Additionally, this language structure also uses some useful operations such as OR and AND that represent MAX and MIN respectively to obtain fuzzy values from the set of rules previously extracted. The Defuzzification process was then performed using appropriate membership function to generate output variables (non-fuzzy values). These variables were introduced into detection sensors for accurate detection of incoming objects on highway.

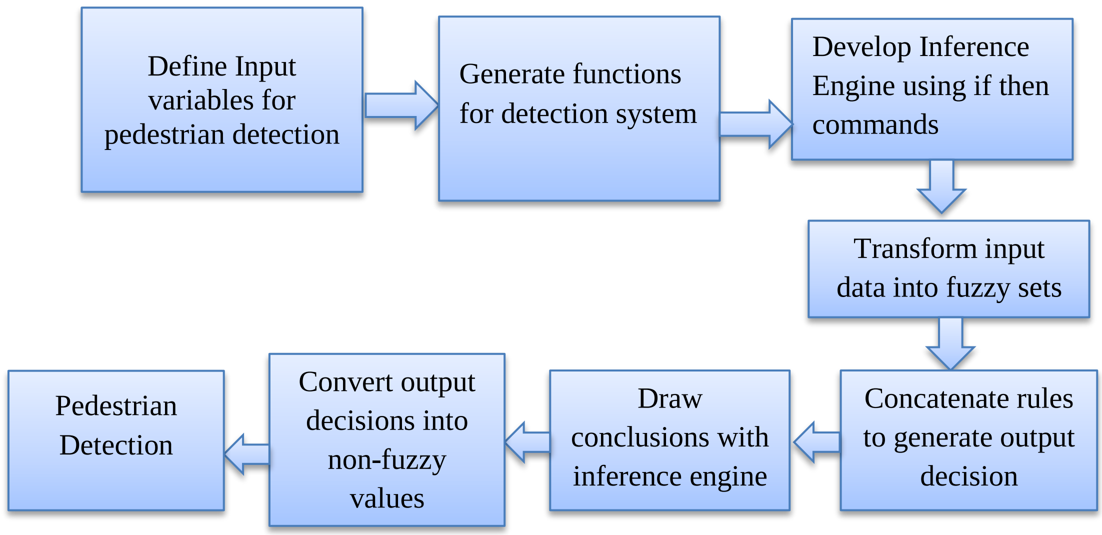

Figure 3: Algorithm for developing detection system

The output of the fuzzy model provides values ranging from 0 to 1(NO and YES), this value stands to indicate if an object exists over the crosswalk. A value very close to zero indicates an obstacle does not exist while a value very close to one (1) indicates an object exists. It now depends on whether the object is a vehicle or pedestrian. If the object detected is a pedestrian, a signal would be sent to the driver in form of LED with different colours indicating how far or near the object is from the driver. On the other hand, the output value of zero means the signaling unit must not be activated while values close to one (1) means the signaling unit must be enabled to alert the driver about the pedestrian detected on crosswalk.

The model should be able to detect pedestrians on the highway and send a signal warning to the driver to reduce its speed or stop completely to avoid collision. The developed system must be able to differentiate between vehicles and pedestrians on the road, when the detection model recognizes the vehicle, it automatically disables the system but if the incoming object is a pedestrian, the system would accept and signal the driver. The combined rules generated in Figure 1 to extract decision were embedded in detection sensors to capture any pedestrian across the highways. The detection system would start to be active when the object or obstruction is about 10 to 20 meters away from the driver.

RESULTS AND DISCUSSION

The first thing is to build an inference model with the input and output variables as outlined in the previous section. Movement and density represent the input variables while pedestrian level (pl) represents the output variable. The second step fuzzified all elements of input and output parameters with five different values assigned to them. For instance, the linguistic variables for the input parameter; movement are free pedestrian movement, reasonably free pedestrian movement, stable pedestrian movement, unstable pedestrian movement and congested pedestrian movement while linguistic variables: Very Low Density, Low Density, Medium Density, High Density, and Very High Density. The pedestrian level, which is the output parameter, was then calculated for each road segment to determine the performance of pedestrian model for the detection. Additionally, the information from the fuzzified inputs were then combined using the if-then rules and the linguistic variables were connected using AND operator. Table 1 demonstrates the meaning of each pedestrian level.

Table 1: Fuzzy inference model output parameter

PL1	Completely Pedestrian free
PL2	Reasonable Pedestrian free
PL3	Stable Pedestrian free
PL4	Unstable Pedestrian free
PL5	Congestion

In order to derive decision from the chains of rules by the output parameters, we need to further combine the features using the If-then rules with AND operator, this process of aggregation is known as de-fuzzification as presented in Table 2.

Table 2: Model rules with AND function

IF	AND	THEN
Movement is free movement	Density is very low	PL is PL1
Movement is free movement	Density is very low	PL is PL2
Movement is stable movement	Density is low	PL is PL3
Movement is unstable movement	Density is high	PL is PL4
Movement is congested	Density is very high	PL is PL5

Lastly, we ran the model to determine the results of different routes to observe traffic behaviour for different experiments that we have put into consideration. The results would help us to know how busy the road is since as the value moves close to zero, the road congestion reduces and vice versa. However, when the value moves close to 1, the road congestion increases. The results in Table 3 show the traffic behavior of the highway for the region considered.

Table 3: Illustrating pedestrian level for input and output variables

Movement	Density	Pedestrian Level
15	19.5	0.61
19	45.6	0.95
17	41.4	0.88
12	85.2	0.54
8	102.4	0.36

In Table 3, the levels of pedestrian are very close to one another, the density input ranges from 19.5 to 102.4; when the movement is 19, the level of congestion is 0.95 (very close to 1), which indicates severe congestion area but when the movement is 8 the level of congestion reduces to 0.36, which indicates congestion-free zones. The closer the congestion to 1 the higher the traffic in that location while the closer the congestion to zero, the less the traffic in that location.

Our results compared favourably with a recently published paper on pedestrian detection; their paper applied multispectral approach to reduce average miss rate by 15% on pedestrian datasets with different number of image frames. However, our paper uses fuzzy logic to develop inference engine with some cascaded rules to detect incoming objects across the road walk; the results achieved can detect objects near or far away from drivers by using embedded sensors in building detection system. While in (Hwang et al., 2015), the approach considered some dataset properties such as scale, occlusion for further analysis of pedestrian positions across the highways. In future, the developed fuzzy inference models in this paper could be used for analyzing pedestrians in multispectral datasets.

CONCLUSIONS

The traffic density and movement traffic have been calculated and applied in this work to determine the behaviour of traffic in those locations of consideration on the highway. The results have shown that the movement on those locations considered is about 5000 pedestrians per hour but it has been assumed that the capacity of each road is around 1500 pedestrians per hour in a less congested area. Additionally, some if-then rules have been specified arbitrarily to combine information from input parameters that would result in fuzzy values. The proposed technique is simple as it applies and follows common logic in developing models for traffic detection. Based on the results obtained, the developed model has been very effective in modeling traffic behavior and transportation process for pedestrian detection on highway.

REFERENCES

Gosaina A, Dahiya S (2016). Performance Analysis of Various Fuzzy Clustering Algorithms. ScienceDirect, 7th International Conference on Communication, Computing and Virtualization. 79(16):100– 111.

Hwang S, Park J, Kim N, Choi Y, Kweon LS(2015). Multispectral Pedestrian Detection, Benchmark Dataset and Baseline. Computer vision foundation. 1037-1045.

Kalinic M, Jukka M, Krisp (2019). Fuzzy inference approach in traffic congestion detection. Annals of GIS. 25(4):

329-336.

Liu Z, Chen Z, Zhanming L, Hu W(2018). An Efficient Pedestrian Detection Method Based on YOLOv2. Mathematical Problems in Engineering.1-10.

Mamdani EH, Assilian S (1975). An experiment in linguistic synthesis with a fuzzy logic controller. International Journal of Man-Machine Studies. 7(1):1-13.

Muthukumar V(2015). Automated Pedestrian Detection, Count and Analysis System. Nevada Ndot Safe and Connected. Carson City. 1-35.

Navarro PJ, Fernández C, Borraz R,Alonso D (2017). A Machine Learning Approach to Pedestrian Detection for Autonomous Vehicles Using High-Definition 3D Range Data. Sensors. 17(18):113-118.

Pavithra PR, Ravichandran KS, Sekar KR, Manikandan R (2018). The Effect of Thermography on Breast Cancer Detection. A multi-faceted Review journal in the field of Pharmacy. 9(1):10-16.

Raj AA (2019). Adaptive Neuro-Fuzzy Inference System-based Nonlinear Equalizer for CO-OFDM Systems. The Computer Journal. 63(2):169–178.

Robert L, Cannon, Dave JV, Bezdek JC (1986). Efficient implementation of the fuzzy c-means clustering algorithms. IEEE transactions on pattern analysis and machine intelligence. 2:248-255.

Ton-That T, Nhan T, Hyung C(2016). An Algorithm for Optimizing Membership Functions of Fuzzy Inference Systems Based On Fuzzy Associative Memory. Journal of Intelligent and Fuzzy System. 27(1):273-285.

Yadav R, Senthamilarasu V, Kutty K, Vaidya V(2015). A Review on Day-Time Pedestrian Detection. SAE Technical Paper. 3-11.

Zhang S, Benenson R, Omran M, Hosang J, Schiele B(2017). How Far Are We From Solving Pedestrian Detection?. Computer Vision Foundation, IEEE Xplore. 1259-1267.