FUZZY EXPERT SYSTEM FOR SEVERITY PREDICTION OF OBSTRUCTIVE SLEEP APNEA HYPOPNEA SYNDROME

C. Zoroglu, and S. Turkeli

***Abstract*—** Polysomnography (PSG) is standard for both OSAHS diagnosis and severity detection, but it has some disadvantages such as requirement for many equipment, conditions and times to get successful measurements. The aim of the study is to design a fuzzy expert system (FES) to predict the severity degree of obstructive sleep apnea hypopnea syndrome (OSAHS). Pre-operation data of 24 patients who had robotic surgery for treatment of OSAHS are used. We divided the data into two: 14 of them for designing the FES and 10 patient data for testing the model. min SpO_2,, BMI, Mallampati score, and neck circumference (NC) information are used as inputs of the system. The output is fuzzified apnea hypopnea index (AHI). Then, this prediction compared with the actual AHI scores of the patients. Classification accuracy for design step is 100% and correlation between our prediction and AHI is 0.89 after removing 4 patients because of missing data. For the test result, classification accuracy is 100% and value of correlation coefficient is 0.82 after leaving one out due to same reason. Our study shows a possibility of simpler alternative to PSG and proposes fuzziness in standard AHI intervals as different point of view.

***Keywords*—** *fuzzy expert system, severity detection, prediction, Obstructive Sleep Apnea Hypopnea Syndrome*

I. INTRODUCTION

OSAHS is an important health problem which results from repetitive obstructions in upper airways. In apnea, respiration completely arrests whereas airflow partly continues in hypopnea [1]. Arrests or reductions in airflow lead to oxygen desaturation in blood, and this in turn, causes arousals. Insufficient sleep may lead to daytime sleepiness, fatigue and even traffic and occupational accidents [2]. Also, it is detected that OSAHS is related to arterial hypertension, hypercoagulability, reduced cerebral perfusion, atherosclerosis, cardiac arrhythmia, coronary artery disease, congestive heart failure, ischemic stroke, axonal peripheral neuropathy and diabetes mellitus [3]. Prevalence of the disease is 4% among middle-aged men, and 2% women in the same age category [4] It is predicted that these ratios increase for 65 age and older [5].

OSAHS is diagnosed and graded by analyzing some physiological parameters such as brain and heart signals, oxygen saturation, airflow, respiratory movements which are obtained in sleep laboratories by means of PSG. Laboratory tests alone are not sufficient for diagnosis. Results must be interpreted by experienced staffs. However, manual scoring of the resulting recording entails too much effort and time to the medical specialists and as a consequence it implies a high economic cost [6]

Among the parameters which are obtained via PSG, AHI is the key one for case identification, for quantifying disease severity. It is defined as the number of apneas and hypopneas per hour of sleep. Cases are graded according to AASM 1999 criteria as follows [7]: AHI<5 and ≤15 as mild; AHI>15 and ≤30 as moderate; and AHI >30 as severe. There are 3 standard hypopnea definitions published by AASM in different years. AHIChicago requires either > 50% airflow reduction or a lesser airflow reduction with associated > 3% oxygen desaturation or arousal. Hypopnea is defined as 30% or more airflow reduction with ≥ 4% desaturation in AHIRecommended. For AHIAlternative, hypopnea is defined as 50% or more airflow reduction with ≥ 3% desaturation or arousal. The cut-points given above are for AHIChicago, and they are used as a standard. However, when these cut-points are not adjusted for other definitions, it is found that approximately 40% of patients previously classified as positive for OSAHS using AHIChicago being negative using AHIRecommende and 25% being negative using AHIAlternative [8]. This indicates the need for more flexible AHI intervals rather than crisp ones.

Expert systems are used for decision making in various fields such as agriculture, chemistry, space technology, geology and medicine [9]. The basic idea behind ES is to transfer the vast body of task-specific knowledge from a human to a computer. This knowledge is then stored in the computer and users call upon the computer for specific advice as needed. The computer can make inferences and arrive at a specific conclusion. Then like a human consultant, it gives advices and explains, if necessary, the logic behind the advice [10]. Zadeh's introduction the fuzzy sets enable to use both numerical and linguistic variables together, and provide expert systems with the ability of human-like reasoning. Therefore, ES can be solution for the problem uncertainty in medical data and its classification which arises from the complex nature of medicine.

The aim of the study is to design a FES to predict the severity degree of OSAHS. Determining OSAHS severity is important because first, it is also an indicator for some of serious health problems such as heart diseases, hypertension and second, there is need for measures to evaluate treatment response. The system uses body mass index (BMI), minimum blood oxygen saturation level during sleep (min SpO_2), Mallampati score and NC as input. Then, we assigned each patient to one of three groups; mild, moderate and severe according to our OSAHS severity predictions. Normal health condition is not considered because the data consist of OSAHS diagnosed patients. Finally, output (i.e. severity of OSAHS) evaluated using AHI and the model tested on the data of another patient group which are not included in design process of the FES.

II. RELATED WORKS

This section includes some of past and current studies about medical applications of FES and the studies which specifically aim to help decision making problems about OSAHS.

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Manuscript received May 10, 2017; accepted Aug 20, 2017.
Digital Object Identifier:

Developments of expert systems in medicine began with the MYCIN system about a decade after Zadeh's introduction of fuzzy logic. Although fuzzy logic was not used in MYCIN, the major role played by uncertainty in medical decision-making is recognized. One of first successful applications of fuzzy logic in medicine was CADIAG where the medical information is derived from medical records taken from a hospital information system. The information is fuzzified and coded in terms of rules. The system uses fuzzy logical inference mechanisms to generate diagnostic information. SPHINX and CLINAID are also early expert systems which utilize fuzzy logic [11]

The success of fuzzy logic for handling uncertainty in medicine and the results obtained when it is used in expert systems causes FES to be utilized in various fields of medicine. Castanho et al., used genetic-fuzzy system to predict the pathological stage of prostate cancer [12] Abdullah et al., used FES for hypertension risk prediction using age, body mass index (BMI), blood pressure and heart rate as input [13]. Riberio et al., evaluated breast cancer risk through age, menopause age, presence of hormone replacement treatment and fuzzy BMI. Then, they expressed the cancer risk by the terms which are moderate, high and very high [14]. Neshat et al., determined liver disorder intensity using BUPA Liver Disorder dataset which contains 345 male patients with 6 numeric attributes [15] Lee and Wang developed an ontology-based FES for diabetes decision support application. This system includes a five-layer fuzzy ontology, fuzzy diabetes ontology, and a semantic decision support agent [16]

Keleş et al., designed neuro FES for diagnosis of breast cancer using data which include 516 benign and 445 malignant masses with 6 features. In neuro FES, as distinct from FES, rules are formed by learning algorithms such as artificial neural network. Also, a user interface is designed to provide ease of use [17]. Oladele et al., used Adaptive Neuro Fuzzy Inference System (ANFIS) for malaria diagnosis. For each patient, an array whose values consist of 1's or 0's according to patient health status is formed. These arrays are inputs of the system and when a person diagnosed as malaria, output is 1, otherwise 0. A hybrid learning algorithm in which both supervised and unsupervised learning algorithms are used together is employed [18].

Allahverdi et al., determined 10-year risk of coronary heart disease for a patient using age, cholestrol level, high density lipoprotein (HDL) level and blood pressure data. Gender and smoking are also important factors but since they have binary values, instead of using them as input, four rules are constructed for all possible situations. According to calculated risk value and level of low density lipoprotein (LDL), system recommends one of three alternatives to physician: 1. patient can keep his/her normal life; 2. change in the diet is required; 3. drug therapy must be applied [19]. Ali Keleş and Aytürk Keleş used a neuro FES (called ESTDD) to diagnose thyroid disease. Data which consist of 215 sample, 3 classes and 5 features are used. The system has also a user interface and a database which stores patient information. Results show that the accuracy of the system is 95.33%. ESTDD can also be used for educational purposes. Randomly selected medical data belongs to each patient is showed on the screen and ESTDD system wants user to diagnose all patient or patients selected by educator. As a result ESTDD system compares user diagnosis with self-diagnosis and real diagnosis if it is previously entered in system and this statistical evaluation is showed at the bottom of the screen [20].

Fuzzy control applications are very common in anesthesia. These studies include monitoring of vital parameter of patients and controlling the drug infusion to maintain the anesthetic level constant. Some of these studies are controlling depth of anesthesia, muscle relaxation, prevention of hypertension during anesthesia and post-operative control of blood pressure. Pump-like function of heart makes it suitable for fuzzy control applications. A fuzzy controller has been implemented for adaptation of the heart pump rate to body perfusion demand by pump chamber filling detection [21]. Another more advanced system, which is based on neural and fuzzy controller for artificial heart, was developed by Lee et al. [22]. Fuzzy control is also used in artificial pancreas studies which play role in the treatment of diabetes. Atlas et al., applied fuzzy logic theory in their artificial pancreas in order to imitate lines of reasoning of diabetes caregivers. This system uses a combination of control-to-range and control-to-target strategies to automatically regulate individual glucose levels [23]

Steinman et al., proposed a framework to track disease stages. The model considers that a disease does not leaps from one state to the next, discretely and without any indication of the forthcoming event, rather, most transitions take their time, taking place gradually and continuously. Therefore, fuzzy sets become appropriate for modelling [24]. Becker et al., proposed an intelligent patient monitoring and alarm system which evaluates a patient's hemodynamic state on the basis of a current vital parameter constellation with a knowledge-based approach in order to support intra-operative monitoring for the anesthesiologist [25]. Keeping the oxygenation status of newborn infants within physiologic limits is a critical task. For this purpose several vital parameters are supervised routinely by monitors, such as electrocardiograph, transcutaneous partial oxygen pressure monitor and pulse oximeter. Each monitor gives an alarm signal whenever an upper or lower limit of the parameter measured is exceeded. However, a considerable amount of false alarms is generated by artefacts, which are attributed mostly to movements of the infants. Wolf et al., developed an automated system based on fuzzy logic to solve this problem [26].

Philips et al., applied a breath test for volatile organic compounds as a predictor of breast cancer to three groups. First two groups consist of asymptomatic women with abnormal mammograms, 51 with and 50 without histologic evidence of breast cancer in a breast biopsy, and third group of 42 age-matched healthy women with no history of breast cancer. Using Interrelation Miner fuzzy logic software, women with breast cancer and age-matched healthy volunteers were randomly assigned to a training set or a prediction set. Having determined the typicality matrices for both controls and breast cancer patients, these matrices are used to calculate the membership degrees of healthy and diseased states. The difference between these memberships degrees are used for breast cancer prediction. The predictive model was tested in the women with abnormal mammograms and no histologic evidence of breast cancer in a breast biopsy. Results show that this model is superior to the discriminant analysis model the authors previously reported [27]. Seker et al., did a study about prognosis which is critical for planning of treatment during different stages of diseases. In the study, fuzzy–nearest neighbor classifier is used to provide a certainty degree for prognostic decision and assessment of the breast cancer markers, and compared with logistic regression and multilayer feedforward backpropagation neural networks. The overall results indicate that the FK-NN-based method yields the highest predictive accuracy, and that it has produced a more reliable prognostic marker model than other two methods [28].

FES is also used for the determination of obstructive and other sleep apnea types. Bonillo et al., diagnosed sleep apnea syndrome by analyzing airflow signal, respiratory movement signals (both thoracic and abdominal) and oxygen saturation in arterial blood. To this end, signals are firstly preprocessed to reduce false positives by determining artifacts in the signals. Possible apneic events are determined according to drops in the amplitudes and interval lengths of the signals. Existence of an apneic pattern is considered when the underlying cause has physiological significance. Physiological events are thought as indicator of apnea, when they occur in a temporal order. Then, apneic patterns are classified as apnea, hypopnea or false positive using fuzzy inference system. In this system, firstly, oxygen desaturation signal of the pattern is evaluated and membership degree for desaturation concept is established with respect to duration and reduction of the desaturation signal. Next, airflow and respiratory signals are evaluated in the same way, and then combining these two results under some rules gives membership degrees for apnea, hypopnea and normal respiration. If the membership degree of normal respiration is less than the others, then this pattern is called apneic event. Lastly, respiratory movement percentage information when an apneic event occurs is used for determining type of sleep apnea [29]

Nazeran et al., developed to detect obstructive sleep apnea by using the respiratory airflow signal in adults. This signal is subjected to a series of processing step, and then areas and standard deviations are calculated for 3-second intervals. Since ranges of these values vary between patients, they are normalized by dividing the areas and standard deviations which are obtained from the first 60 or 120 seconds of normal breathing signals from each patient. Normalized areas and standard deviations are used as the inputs of the fuzzy systems. Membership functions of these inputs are derived from apnea and hypopnea events of four patients. Mamdani method is used for fuzzy inference. Lastly, the centroid method was utilized in the defuzzification stage to give the final crisp outputs [30]. Aims of this and former studies are to detect apnea/hypopnea events from physiological signals and to help or to automatize the scoring process. Nevertheless, the two studies require for PSG device. Polat et al, classified OSAS patients with respect to degree of disorder using ANFIS and one against all method. The parameters which are obtained from PSG are arousals index, AHI, min SpO_2 in stage of REM, and percent sleep time in stage of oxygen saturation intervals bigger than 89%. Role of one against all method is to solve the problem of dealing with multi class since ANFIS alone gives output with one class [31]. This study also uses only PSG data and its success heavily depends on the PSG success.

There are some studies which uses equations to predict OSAHS probability and sleep apnea clinical score. These models utilize self-reported OSAHS symptoms combined with demographic and anthropometric variables to discriminate between patients with and without OSAHS. Rowley et al., studied the utility of four clinical prediction models for either predicting the presence of obstructive sleep apnea (OSA, apnea-hypopnea index, or prioritizing patients for a split-night protocol and found that these models were not be sufficiently accurate to discriminate between patients with or without OSAHS but could be useful in prioritizing patients for split-night PSG [32]. Some studies attempted to predict AHI from nocturnal pulse oximetry measurement due to simplicity of its application with respect to PSG. Magalang et. al., compared the relative usefulness of the different indexes derived from pulse oximetry in the diagnosis of obstructive sleep apnea, and to determine if a combination of these indexes improves the prediction of the apnea-hypopnea index (AHI) measured by polysomnography [33]. Marcos et. al., estimated AHI by extracting time-domain and frequency-domain features from oximetry data and constructed relationship between these features and actual AHI using multiple linear regression and multilayer perceptron [34]. However, these methods are focusing only on oxygen saturation data which is actually determined or affected by risk factors of OSAHS such as obesity, tonsil size.

III. REASONS OF NEED FOR FUZZY LOGIC IN MEDICINE

Although it had been studied since the 1920s, as infinite-valued logic, the term fuzzy logic was introduced with the 1965 proposal of fuzzy set theory by Lotfi A. Zadeh [35]. As distinct from the classical (crisp) sets which use 0 and 1 to represent membership of an element, in fuzzy sets a degree of membership, which is in the interval [0, 1], is assigned by a membership function. For instance, 400C can have membership degree for both “moderate temperature” and “high temperature” fuzzy sets. This assigning process depends on application. As seen from the example, fuzzy sets make it possible to use natural language in computations. We generally use vague terms such as cold weather, high fever, etc. to express our daily problems. The power of fuzzy logic lies here: it provides human-like reasoning to solve problems. There are some sources of uncertainty in medicine which make appropriate the use of fuzzy logic [36]:

- The medical history of the patient is given by the patient himself. It is highly subjective and may include simulated, exaggerated, or understated symptoms.
- Indications can be misinterpreted because the boundary between normal and pathological status is not always clearly defined.
- Measurement errors, organizational problems (mislabeling samples, sending them to the wrong laboratory, etc.) may occur in laboratory tests.

IV. METHOD

This research was performed in accordance with relevant guidelines and regulations, adhered to ethical research standards set by the latest revision of the Declaration of Helsinki, was approved by Bakırköy Dr. Sadi Konuk Training and Research Hospital Department of Otolaryngology, and informed consent was obtained from all subjects. In this study, pre-operation data of 4 female and 10 male patients who had robotic surgery for treatment of OSAHS are used. All

 ISSN: 2548-0650 http://dergipark.gov.tr/jcs

individuals were diagnosed as OSAHS after PSG. We used min SpO_2, BMI, Mallampati score, and NC information as input to predict OSAHS severity and compared the result with AHI scores of patients. Also, we tested our FES with 10 patients (two of them are women) which were not used in design process. Table I summarizes patient information for design and test group. We did not use Epworth Sleep Scale (ESS) because there is no significant correlation between the ESS score and the AHI [37] and age, since the relation between age and severity is not certain [1]. In the following, some concepts are defined. Then, design process of FES is explained as well as providing some fuzzy logic background.

Table I. Summary of patient information.

	Design	Test
Number of patients	14	10
Age	52±7.42	50±8.12
min SpO_2	82.4±7.84	77.8±6.27
BMI	32.5±5.48	28.5±5
ESS	11±4.6	13.6±1.43
NC	41±3.22	40±2.86
AHI	28±18.28	26.9±12.47

Definitions

Apnea: It is the cessation of airflow at least 10 seconds.

Oxygen desaturation: It is the reduction of blood oxygen saturation below the 90% or dip into 3% or more from the baseline. Baseline is defined as the mean amplitude of stable breathing and oxygenation in the two minutes preceding onset of the event (in individuals who have a stable breathing pattern during sleep) or the mean amplitude of the three largest breaths in the two minutes preceding onset of the event (in individuals without a stable breathing pattern) [7].

Mallampati score: The score is assessed by asking the patient to open his or her mouth as wide as possible, while protruding the tongue as far as possible. A standard I to IV grading system is used (Figure 1).

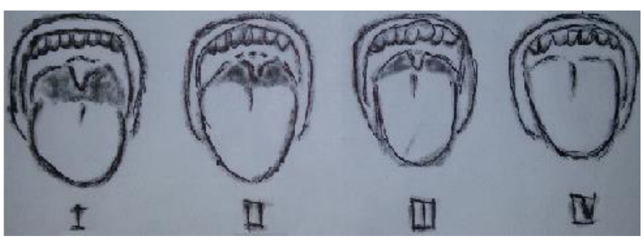

Fig. 1. Mallampati airway classification. Class I: soft palate and entire uvula visible; Class II: soft palate and portion of uvula visible; Class III: soft palate visible (may include base of uvula); Class IV: soft palate is not visible. C. Z. drew the figure.

FES Design

Typical FES architecture is shown Figure 2. In the following, components of our FES are examined. All these steps are performed using the Fuzzy Inference System (FIS) tool of Matlab version of R2013a.

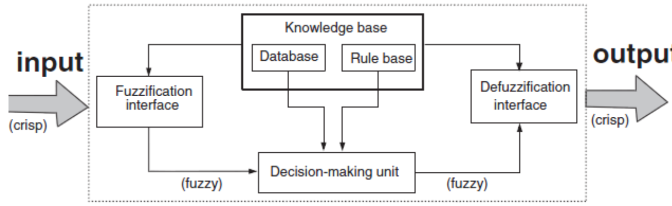

Fig. 2. Fuzzy system and its components[38].

Fuzzification

Fuzzification is the process where the crisp quantities are converted to fuzzy (crisp to fuzzy). By identifying some of the uncertainties present in the crisp values, the fuzzy values are formed. The conversion of fuzzy values is represented by the membership functions. Figure 3, 4, 5, 6 and 7 shows fuzzified inputs of min SpO_2, BMI, Mallampati score, NC and the output.

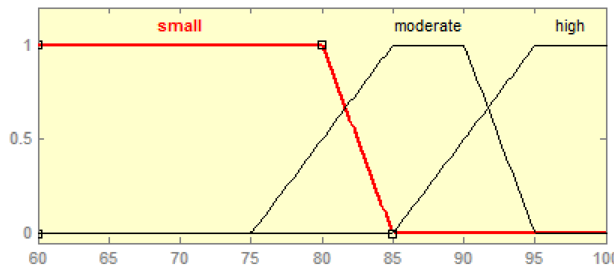

Fig. 3. Membership functions and corresponding linguistic variables of 'min SpO_2'.

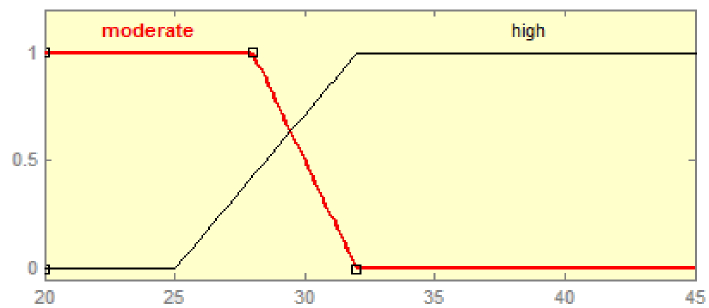

Fig. 4. Membership functions and corresponding linguistic variables of 'BMI'.

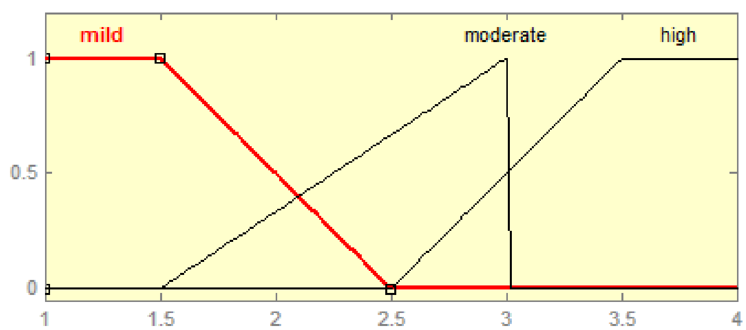

Fig. 5. Membership functions and corresponding linguistic variables of 'Mallampati score'.

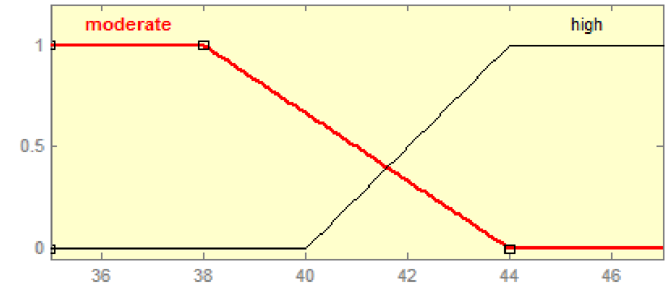

Fig. 6. Membership functions and corresponding linguistic variables of 'NC'.

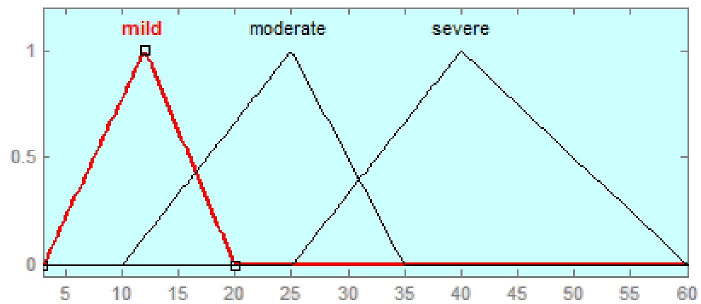

Fig. 7. Membership functions and corresponding linguistic variables of 'Severity'.

Construction of Rules

Rules are the required components together with the inputs to inference. They are in the form of "If x is A, Then y is B". Here, x and y are the linguistic variables, A and B are the linguistic terms. "If" part of rule called antecedent, and "Then" part is called consequent. Rules are formed either by consulting a domain expert or based data using methods such as artificial neural network or genetic algorithm. Since our data is not sufficient for the latter ones, we constructed the rules by referring otolaryngology experts. Figure 8 shows the formed rules.

1. If (SpO is small) and (BMI is high) then (Severity is severe) (1)
2. If (SpO is moderate) and (BMI is high) and (Mallampati is moderate) and (NC is high) then (Severity is severe) (1)
3. If (SpO is small) and (BMI is moderate) and (Mallampati is high) and (NC is high) then (Severity is severe) (1)
4. If (SpO is high) and (BMI is moderate) and (Mallampati is high) and (NC is moderate) then (Severity is moderate) (1)
5. If (SpO is moderate) and (BMI is moderate) and (NC is moderate) then (Severity is moderate) (1)
6. If (SpO is small) and (BMI is moderate) and (Mallampati is high) and (NC is moderate) then (Severity is moderate) (1)
7. If (SpO is small) and (BMI is moderate) and (Mallampati is mild) and (NC is moderate) then (Severity is moderate) (1)
8. If (SpO is moderate) and (BMI is high) and (Mallampati is mild) and (NC is high) then (Severity is moderate) (1)
9. If (SpO is moderate) and (BMI is high) and (Mallampati is high) then (Severity is moderate) (1)
10. If (SpO is high) and (BMI is moderate) and (Mallampati is moderate) and (NC is moderate) then (Severity is mild) (1)
11. If (SpO is moderate) and (BMI is moderate) and (Mallampati is moderate) and (NC is moderate) then (Severity is mild) (1)
12. If (SpO is high) and (BMI is high) and (Mallampati is high) and (NC is high) then (Severity is severe) (1)
13. If (SpO is moderate) and (BMI is moderate) and (Mallampati is high) and (NC is high) then (Severity is moderate) (1)
14. If (SpO is high) and (BMI is moderate) and (Mallampati is mild) and (NC is high) then (Severity is moderate) (1)
15. If (SpO is high) and (BMI is high) and (Mallampati is high) and (NC is high) then (Severity is moderate) (1)
16. If (SpO is high) and (BMI is high) and (NC is moderate) then (Severity is mild) (1)

Fig. 8. Rules of our FES. Numbers in the parenthesis refer the weight of that rule. Here, all rules are equally weighted.

Inference

Inference is a process of finding a fuzzy consequent based upon inputs and rules. Each rule gives a result for given inputs and all of these results are aggregated to obtain a combined result. We used Mamdani method for inference. Figure 9 shows graphically how the method works.

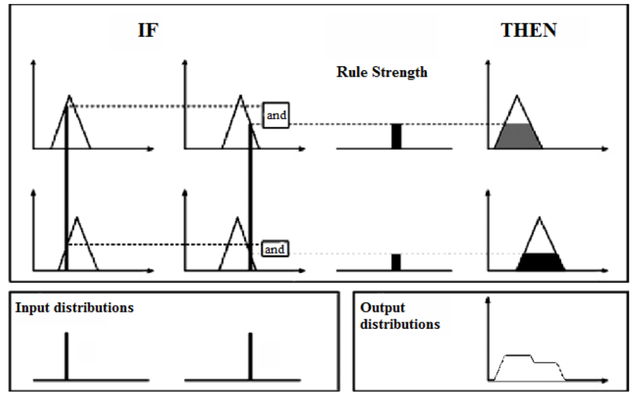

Fig. 9. Graphical representation of Mamdani method [38]. Columns of first box correspond to fuzzy sets and rows correspond to rules. Each input fires a rule to some extent and minimum strength determines the output. Aggregated output, which is the final result, are obtained by combining maximum part of individual rule outputs. For that reason, Mamdani method is also called as max-min method.

Defuzzification

The former step gives a fuzzy output; however, in practice a single result is needed. Defuzzification is the step of converting fuzzy result to a crisp one. We used centroid method to find final output. Calculation of centroid is:

$$z^* = \frac{\int z\mu_B(z)dz}{\int \mu_B(z)dz}, \mu_B \qquad \textbf{(1)}$$

μ_B is the degree of membership of z over fuzzy set B.

V. RESULTS AND DISCUSSION

Results for First Patient Group

Table II shows both the data of the first group (design) and the AHI predictions for each of them. We correctly classified 11 of 14 patients according to disease severity and correlation coefficient between actual AHI of the patients and our prediction is 0.61. This low correlation results from some inconsistencies between actual AHI and the values of data for patients 5, 11, 12, 13. Therefore, we got opinions of domain experts to illuminate the cause of these differences. They explained that obstructions in soft palate, oropharynx and epiglottis cause these differences. Thus, we excluded these patients since we have no appropriate data to add mentioned obstructions to the design.

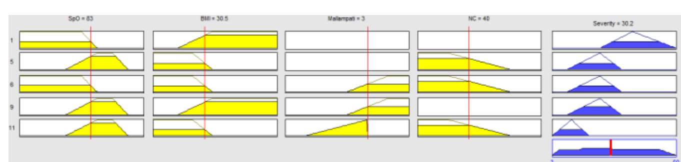

Fig. 10. Fired rules for patient 14. Each row corresponds to the rules (1., 5., 6., 9.,11.) and columns correspond to inputs and the output. The graph in right bottom shows the defuzzification result. Here BMI and tonsil size are more influential than other factors on severity result.

After these exclusions, classification accuracy rises 100%, and correlation coefficient becomes 0.89. Figure 10 shows the fired rules which determine the severity for patient 14

Table II. Patient data and predictions.

Pat.	min SpO_2(%)	BMI (kg/m2)	Mall. Score	NC (cm)	AHI	Pre.
1	82	41.6	4	45	27.1	34.3
2	87	26.4	3	36	13	19.0
3	91	27.3	3	37	11.4	17.9
4	75,3	32.08	2	39	71.2	41.7
5	81	32.8	4	43	19.8	23.3
6	90	24.5	3	40	19.5	18.3
7	79	31.6	2	45	40.4	41.7
8	88,4	27.6	3	38	21.5	17.9
9	81	40.6	3	46	62	42.3
10	85	28.8	1	42	21.5	19.9
11	88,4	35.6	2	43	20	33.0
12	82	38	4	41	10.1	24.7
13	60	38.1	3	45	22.1	35.1
14	83	30.5	3	40	33	27.8

Test Results

Prediction results for test step are shown in Table III. Classification accuracy is 90% and value of correlation coefficient is 0.58. Inconsistency problem here, which is in patient 5, is also available. After leaving this patient out, accuracy and correlation coefficient become 100% and 0.82.

Table III. Predictions for test data.

Pat.	min SpO2(%)	BMI (kg/m2)	Mall. Score	NC (cm)	AHI	Pred.
1	81	28	2	37	23.7	27,8
2	75	29	4	37	25	32,8
3	87	24.5	3	37	13.8	18,4
4	68	28	3	40	40.9	35,1
5	72	41	2	41	15	41,7
6	78	26	4	44	52	38,4
7	86	27	3	39	15.4	18,8
8	75	31.3	4	45	32.7	41,7
9	73	28	4	42	31.2	37,9
10	82.64	22.6	2	40	19	21,6

When the tables are examined, some extreme AHI values such as 71.2, 62 are seen and our predictions do not close these numbers. Actually, what we try to do here is not to exactly find the AHI values; instead, our focus is to correctly classify the patient with consistent results. Also, we aimed to show that standard AHI intervals for severity classification may not be so crisp, as it is now. For instance, AHI value of patient 1 in train set is 27.1 which mean the patient has moderate OSAHS. However, our prediction, 34.3, indicates that the patient has more severe OSAHS than moderate since 34.3 has also a membership degree in “severe” fuzzy set. Support for this prediction comes from intrinsic challenges of PSG. In order to obtain accurate AHI, these minimal conditions have to be provided: sound proof and climatized room that can be kept in complete darkness, a comfortable bed and the technical installations for recording the biological signals, avoiding the patient from the use of sleeping pills or narcotics several days before the study and from strenuous physical exercise on the day of the study, and not to drink coffee, black tea or alcoholic beverages [39]. Insufficiency in one of these conditions may result in misleading AHI result by reducing sleep quality. Moreover, OSAHS may be result from sleeping in supine position and it is shown that PSG may overestimate the severity of OSAHS in some patients with positional OSAHS [40].

VI. Conclusions

In this study, we determined severity degree of OSAHS by means of min SpO_2, BMI, Mallampati Score, NC and evaluated the predicted results with AHI. Results show that fuzzy logic can be successfully applied for that problem. Although, we obtained the min SpO_2 data from PSG, it is possible to get this data by nocturnal pulse oximetry which is readily available, relatively inexpensive and can be easily done at home. Our study shows a possibility of simpler alternative to PSG and proposes fuzziness in standard AHI intervals as different point of view. Powerful visualization ability of Matlab also contributes our study. For example, Figure 10 helps to see which risk factor predominates on the severity condition and this may direct the decision about treatment. In a later study, we are planning to test our model on more patient data which no PSG is used for any part of data collection process. Also, we aim to integrate our FES with hospital information system by which a risk evaluation can be done automatically using available patient information without requiring separate data collection. This system will be able to warn physician to further investigate OSAHS risk as well as affecting his/her medical decision about the treatment of current disease of the patients.

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ACKNOWLEDGEMENT

The authors gratefully acknowledge Hakan Kaya, M.D., and Fatma Tülin Kayhan, M.D., who contributed the study with their expertise.

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