Fuzzy Set Training for Sleep Apnea Classification

Douglas E. Dow

Department of Electrical Engineering and
Technology Wentworth Institute of Technology
550 Huntington Avenue
Boston, Massachusetts, 02115, USA
dowd@wit.edu

Isao Hayashi

Faculty of Informatics
Kansai University
Takatsuki, 2-1-1, Ryozenji-cho
Osaka, 569-1095, Japan
ihaya@cbii.kutc.kansai-u.ac.jp

Abstract—**Untreated sleep apnea may result in higher risk for daytime drowsiness, heart conditions, high blood pressure, stroke, reduced cognitive function, and development of dementia. Polysomnography is the primary diagnostic tool for sleep apnea, but the cost and uncomfortable environment hinder diagnosis in many individuals. Home-based sleep monitoring systems would increase accessibility and comfort, but require robust signal analysis for quality analysis. Machine learning has been applied for sleep apnea classification, but more improvements would enhance effectiveness. In this study a Fuzzy set system with tuning was developed for classification of sleep apnea or hypopnea events during sleep for individuals at risk of sleep apnea. Annotation files from a sleep study available on Physionet database were analyzed for classification of sleep disruption events. The performance of the developed fuzzy set algorithm was compared with classification by other machine learning algorithms using the Weka system. Improved algorithms for classification of sleep events would be useful toward development of sleep monitoring systems that potentially would encourage individuals with sleep events to seek treatment.**

Keywords—respiration; hypopnea; sleep monitoring; physionet; machine learning; self adaptation; tuning; supervised training; python

I. Introduction

Sleep apnea is a common sleep disorder which results in periods of cessation or reduction of breathing during sleep [7] . The incidence of sleep apnea increases with old age and obesity. Sleep apnea is associated with increased risk of daytime drowsiness, heart conditions, high blood pressure, stroke, reduced cognitive function, and development of dementia [19, 25].

A polysomnogram is the primary assessment for clinical diagnosis of sleep apnea [13]. Polysomnography is expensive [22], which may limit access for diagnosis and potential treatment for many individuals. Polysomnography typically records 12 or more electrical signals from sensors on the body during an extended period of sleep. Each of the channels typically have multiple wires between the sensor and a central controller unit. Many individuals find the attached sensors and wires to interfere with sleep by lowering their comfort level or free movement [5]. Some individuals also have trouble relaxing for sleep due to the clinic environment, including having medical staff around. The quality of the assessment would be impaired if the sleep pattern is much disturbed from their normal sleep pattern.

Efforts have been made to diagnose for sleep apnea without undergoing a full polysomnography session [5, 7, 22, 23]. These efforts usually attempt to analyze a smaller set of recorded signals or take place in a more natural setting, such as using primarily audio sounds [24], a standard hospital patient monitor [1], or at-home sleep monitoring [3, 5, 18, 22]. These alternative methods show promise, but more development of signal processing for classification would enhance diagnostic value.

Compared with a polysomnography done in a clinical setting, a home-based system would have less control of the recording conditions, sensors and sources of potential noise artifacts. Thus, algorithms used to analyze measurements in home-based systems would need to be more robust and adaptive. Machine learning algorithms may provide a way toward more robust analysis of sleep monitoring signals.

Some work applying machine learning for sleep monitoring has been reported [7, 16] and shows promise. Expert system rules have been applied for sleep classification [2]. Fuzzy logic methods have been applied to analysis of physiological data [4, 8, 10, 16].

In a previous study, a fuzzy logic with tuning

system was used for training with scalar parameters and output values [8]. The algorithm was used for prediction of age of rats based on properties of the muscles. In the current study, that algorithm was adapted to classify the outcome to discrete sets. The training was accomplished based on scalar error values. Once the training was completed, the testing phase would classify the resulting scalar output value to one of the discrete classes. This system was utilized to analyze recorded sleep events, and to classify each event as a hypopnea, apnea or other possible event. The performance of the algorithm was compared with classification by other machine learning algorithms using the Weka system [8, 9]. Such algorithms for classification of sleep events would be useful toward development of sleep monitoring systems that potentially would encourage individuals with sleep events to seek treatment.

II. MATERIALS AND METHODS

A. Data Preparation of Sleep Apnea Events

The data that was used for training and testing of the algorithm was derived from the publically available database of Physionet (www.physionet.org) [14]. The data had been recorded during a sleep study conducted by St. Vincent's University Hospital under the University College Dublin Sleep Apnea Database (UCD). The UCD consists of recordings made during an overnight polysomnogram session. The UCD data used for this study consisted of the annotation files that were made for each polysomnogram session. These annotations were made by an experienced sleep technologist who analyzed the recorded signals of the polysomnogram to detect sleep events, and then made annotations for each event. The annotation files are included in and accessible from the UCD of physionet.

Each observed sleep event was classified by the sleep technologist as either a hypopnea or an apnea event. A cessation of breathing for at least 10 seconds is generally considered apnea, but the classification for the annotations involved many signals and measurements of the polysomnography recorded signals. Hypopnea is a less severe disruption of respiration during sleep, for which the breathing is overly shallow or the respiratory rate is abnormally low [2]. The **x** vector inputs used for training and testing were derived from data in the annotation file. The utilized annotation data for each sleep event consisted six values for observations that occurred during the event or where attributable to the event. The six values for observations consisted of 1) the duration of the event in seconds, 2) desaturation level as lowest oxygen saturation (spO$_2$), 3) percent drop in spO$_2$,

4) existence of arousal (binary), 5) heart rate in beats per minute for the Bradycardia-Tachycardia effect, and 6) the percent change in heart rate as a percent.

These parameters of the annotation files have dynamic relations with hypopnea or apnea events during sleeping [6, 13]. A primary function of respiration is the exchange of oxygen and carbon dioxide between the external air and internal blood that is circulating through the tissues. This exchange of gases is hindered during the hypopnea or apnea events. During an apnea that has no cycle of inspiration and expiration, the only gas exchange is between the amount of air remaining in the lungs and the circulating blood. During a hypopnea event, some inspiration and expiration cycles may occur, but at a shallow depth or slow rate, such that an insufficient exchange of gases occurs. The longer the duration of the event, the greater the impairment in gas exchange, which would be reflected in lower spO$_2$ values. A spO$_2$ value that falls too low would indicate threat to the survival of tissue, especially brain and cardiac muscle. Hypopnea and apnea events also affect heart rate and are linked to cardiac arrhythmias [15]. The impaired breathing lowers spO$_2$ and induces a sympathetic response that slows heart rate below normal (bradycardia). Once respiration resumes the heart rate speeds up above normal (tachycardia) to increase spO$_2$ back toward the physiological set point. The low rate of bradycardia and associated percent drop in heart are recorded in the annotation file for each observed sleeping event. Moreover, the process of resuming respiration may often involve arousal from sleep.

To form the **x** vector for the training and testing, each of the utilized values from the annotation files needed to be in the form of a number. All were used as the number value reported in the annotation file, except the binary values for arousal were converted to number values, such that a 1 indicated existence of arousal, and a 0 indicated nonexistence. Some fields were left blank in the annotation file. These events with blank fields were not used in the analysis for this study.

The annotation file included a classification for each event, either HYP for hypopnea, APNEA for sleep apnea, or POSSIBLE. The POSSIBLE notation was occasionally used, probably to indicated what appeared to be a sleeping event but one that could not be distinctly classified as either HYP or APNEA. A number value was assigned for each case, such that -1 was for HYP, +1 was for APNEA, and 0 for POSSIBLE.

Training and testing data sets were derived from

the annotation files of four patient polysomnograms. The patient files were ucddb002, ucddb019, ucddb24, ucddb26. The sleep events for each patient were divided in half and placed into either the training set or the testing set. For some of the patients, the first half of the events were placed into the training set, and for others the second half of the events were placed into the training set. All together the four patients had 469 sleep events, with 236 events in the training set and 233 events in the testing set. The events with blank fields were then removed. For training, an equal number of HYP and APNEA events was utilized. The utilized training set had 40 events, and the testing set had 28 events.

B. Fuzzy Set Tuning Algorithm for Training

For a training set consisting of input **x** vectors and matching output y values, a fuzzy set model was developed during a supervised training session by the fuzzy set tuning algorithm described below. This algorithm was based on prior developments [8, 12, 17, 20, 21]. Key details are described here.

One **x** vector of input numerical values has m values, which were expressed as x_0, x_1 through x_{m-1}. The output numerical value was expressed as y. Fig. 1 shows the utilized membership function, which was an isosceles triangle centered on a_{ij} and having a width of b_{ij}. For an input value of x_j, the membership value of A_{ij} was calculated as follows.

$$A_{ij}(x_j) = 1 - \frac{2 \cdot |x_j - a_{ij}|}{b_{ij}} \tag{1}$$

Where A_{ij} was the membership value for an x_j input value. The j indicated which of the **x** input (x_0, x_1, … x_{m-1}), and the i indicated which fuzzy rule (f_0, f_1, … f_{q-1}). Any value of A_{ij} less than 0 was nullified (set to 0).
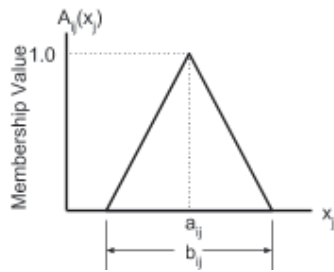

Fig. 1. Fuzzy set membership function. Function maps an input x_j value to the membership value that ranges from 0 to 1. Shape of the function was an isosceles triangle with height of 1.0, width of b_{ij} and centered at a_{ij}. Values of x_j that were outside of $a_{ij} \pm (b_{ij}/2)$ were mapped to 0.

Each of the x_j inputs had p membership functions to classify the x_j value. The number of fuzzy rules in the model was determined as follows.

$$q = p^m \tag{2}$$

where q was the number of fuzzy rules. The output of applying all q fuzzy rules was determined as follows.

$$\mu_i = \prod_{j=0}^{m-1} A_{ij}(x_j) \tag{3}$$

$$y = \frac{\sum_{i=0}^{q-1} \mu_i \cdot w_i}{\sum_{i=0}^{q-1} \mu_i} \tag{4}$$

where μ_i was the product of each membership value for a fuzzy rule, and y was the output of applying all fuzzy rules to an input **x** vector. The y value was a scalar number.

The method of training the membership functions for supervised learning was denoted as self-tuning [8, 20, 21], and was based on maximum descent [12]. A training set of n **x** vectors was utilized, including vectors x_0, x_1, … x_{n-1}. The output of applying one x_k vector to all the fuzzy rules was y_k. The error value for one x_k vector applied to one rule to determine y_k was calculated as follows.

$$E_k = \tfrac{1}{2} \cdot (y_k - y_k^r) \tag{5}$$

where y_k^r was the desirable or correct output value, used for supervised training.

The gradients in the error for each tuning parameter were calculated based on an input x_k vector, as follows.

$$\frac{\delta E_k}{\delta w_i} = \frac{\mu_{ki}}{\sum_{i=0}^{n-1} \mu_{ki}} \cdot (y_k - y_k^r) \tag{6}$$

$$\frac{\delta E_k}{\delta a_{ij}} = \frac{\mu_{ki}}{\sum_{i=0}^{n-1} \mu_{ki}} \cdot (y_k - y_k^r) \cdot (w_i - y_k) \cdot s(x_{kj} - a_{ij}) \cdot \frac{2}{b_{ij} \cdot A_{kij}(x_{kj})} \tag{7}$$

$$\frac{\delta E_k}{\delta b_{ij}} = \frac{\mu_{ki}}{\sum_{i=0}^{n-1} \mu_{ki}} \cdot (y_k - y_k^r) \cdot (w_i - y_k) \cdot \frac{1 - A_{kij}(x_{kj})}{b_{ij} \cdot A_{kij}(x_{kj})} \tag{8}$$

where s(g) was +1 if g was greater or equal to 0, and -1 if g was less than 0.

During training, one x_k vector was processed during each timing step. The tuning parameters were updated after processing each input x_k vector from one training step (t) to the next (t+1) as follows.

$$w_i(t+1) = w_i(t) - K_w \cdot \frac{\delta E_k}{\delta w_i} \tag{9}$$

$$a_{ij}(t+1) = a_{ij}(t) - K_a \cdot \frac{\delta E_k}{\delta a_{ij}} \tag{10}$$

$$b_{ij}(t+1) = b_{ij}(t) - K_b \cdot \frac{\delta E_k}{\delta b_{ij}} \tag{11}$$

Each $\mathbf{x}_k$ vector in the training set was processed by the fuzzy rules. After processing each $\mathbf{x}_k$ vector, the fuzzy membership parameters (w_i, a_{ij}, b_{ij}) were adjusted according to eq. 9-11. The sequence of these tuning steps is further described below.

An *iteration* was one pass through all n of the $\mathbf{x}_k$ vectors in the training set. A total error, S, for one iteration was calculated by summing up all of the absolute values of the E_k values as follows.

$$S = \sum_{k=0}^{n-1} |2 \cdot E_k| \qquad (12)$$

The improvement in S from one iteration to the next iteration is I, where I is the difference of the value of S from the prior iteration and the value of S from this iteration.

$$I(t) = S(t-1) - S(t) \qquad (13)$$

The iterations of training stop when the value of the improvement, I, is less than a threshold value T.

Training had two halves. During the first half, the fuzzy parameter of w_i values were tuned according to eq. (6) and (9). During this first half, iterations of tuning occurred until the level of improvement, I, was less than the threshold, T. Then, during the second half, the fuzzy parameters of a_{ij} and b_{ij} were tuned according to eq. (7-8) and (10-11).

The fuzzy set model consisted of the **a** matrix containing the membership center points, the **b** matrix containing the membership widths, and the **w** array containing the weights for each rule. During training, the value of S was monitored. Models at the end of an iteration with an S value that did not show sufficient improvement, were discarded. The final trained model was the one with the lowest S value that did show sufficient improvement. For this model, the **a** and **b** matrix, and **w** array were saved to be used during testing.

The initial position of the membership functions was determined by the range of values of each **x** input variable to be trained. The membership functions were distributed evenly across the range with about one quarter overlap on each side and also beyond the maximum and minimum values. The initial value of the w array was the inverse of the number of **x** vectors.

C. Training and Testing

For training of the fuzzy set tuning model, the inputs were the six number values that formed the **x** vector, and the output type y. The y output type had three values of -1 for HYP, +1 for APNEA, and 0 for POSSIBLE. During training, the algorithm adjusted the parameters of the fuzzy set model to minimize differences between the output y value

predicted by the algorithm, and the correct y value as derived from the annotation file. The y values predicted by the algorithm were scalar numbers, not yet mapped to the classifications.

The process of training formed a fuzzy set model. This trained model was then tested to see how accurate the predictions were for the type of event. During testing, an **x** vector from the testing set would be applied to the trained model, resulting in a y prediction as a scalar number. However, instead of comparing the predicted and correct y values as a number difference as was done during training, the predicted y value was mapped to one of the three event types. Predicted y values of -0.15 or lower were mapped to integer -1 for HYP, values of +0.15 or above were mapped to integer +1 for APNEA, otherwise the value was mapped to integer 0 for POSSIBLE.

Percent Correct was the primary measure of how well a trained fuzzy set model was able to classify a testing set of data. For all the **x** vectors in a testing set, the number of classification errors (v) was found. Percent Correct (PC) was calculated as follows.

$$PC = (1.0 - (\tfrac{v}{n}))$$

where v was the number of classification errors for a testing set, n was the number of **x** vectors in the testing set, and PC was expressed as a percent.

D. Comparison to Other Algorithms

The results of the trained fuzzy set algorithm was compared to results by other machine learning algorithms for the same training and testing data sets. Weka is an open source, publicly available machine learning workbench (University of Waikato, http://www.cs.waikato.ac.nz/ml/weka/) [9, 11]. Several of the available machine learning algorithms were selected in Weka, and listed in Table I. These algorithms were used with their default parameters on the same training and testing data sets. The resulting Percent Correct was recorded.
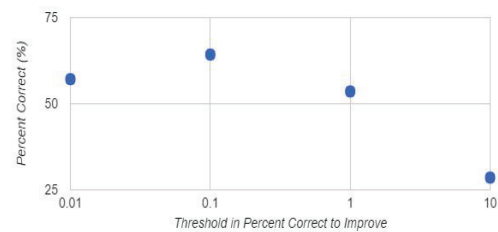

Fig. 2. Threshold of improvement for training to continue. The number of membership functions was 3. The tuning variable K_w was 0.1, and both K_a and K_b were 0.01.

III.   Results

The developed fuzzy set and tuning system was applied to the training set of sleep events for supervised learning. Afterwards, the trained model was applied to the testing set of sleep events. Several of the parameters of the model were varied in order to determine fuzzy set tuning parameters that maximize percent correct for the sleep event data sets.

The threshold for the smallest improvement that was allowed for training to continue was varied and plotted in Fig. 2 with the resulting Percent Correct. A thresholds of 0.1 seemed to work the best.

The number of p membership functions per input x parameter was varied and plotted in Fig. 3, with the resulting Percent Correct. Two membership functions seemed to work the best.

Fig. 3.   Number of membership functions per input x parameter. The threshold was 0.1. The tuning variable K_w was 0.1, and both K_a and K_b were 0.01.

The tuning variable of K_w was varied for a range of values and plotted in Fig. 4. This parameter affects how much the fuzzy model variable w can change for one input **x** vector, as in eq. (9). Thus, the value is scaled for the number of **x** vectors. In the Figures, the value was normalized as if 100 input **x** vectors. A Value for K_w of 0.1 seemed to work the best.
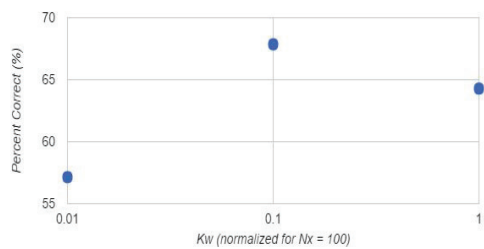

Fig. 4.   Tuning variable K_w and resulting Percent Correct. The number of membership functions was 2. The tuning variable K_w was 0.1, and both K_a and K_b were 0.01.

The performance of the developed fuzzy set tuning system was compared to several other machine learning algorithms using the open source Weka library. Results are shown in Table I.

IV.   Discussion

A fuzzy set and tuning system was developed and tested on data of sleep events that was derived from all night polysomnogram recordings. Annotations of these sleep events were used for training and testing. The annotations files were part of the Physionet UCD database [14]. The input values for each sleep event were 1) the duration of the event in seconds, 2) desaturation level as lowest oxygen saturation (spO_2), 3) percent drop in spO_2, 4) existence of arousal (binary), 5) heart rate in beats per minute for the Bradycardia-Tachycardia effect, and 6) the percent change in heart rate as a percent.

TABLE I.   Comparison with Weka Machine Learning Algorithms

Classify Method (Weka or this study)	Percent Correct (%)
Multilayer Perceptron	75.0
KStar	60.7
Decision Table	64.3
Decision Stump	64.3
Fuzzy Set Tuning (this study)	67.9

The developed fuzzy set tuning algorithm was able to be trained to make a model. The model was then used to classify the type of sleep event, whether hypopnea, sleep apnea or possible (indefinite). The Percent Correct for the testing data set was 67.9%. This was worse than the 75% correct result of the Multilayer Perceptron on the Weka system, but was better than other tested algorithms, such as KStar, Decision Table, Decision Stump.

More testing will be required to verify robustness of the algorithm for sleep event annotation data from other patients. More robust classification of sleep events would aid the development of home based sleep monitoring systems. Such systems would help diagnose individuals in their regular place and pattern of sleeping, possibly leading to better diagnosis. Many individuals who may have sleep apnea are undiagnosed and thus untreated. Better diagnosis and treatment would enhance the quality of life for many people who experience sleep apnea.

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