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Automatic Sleep Scoring System and its Stages Using Electromyography Signal and ANN – A Review

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***Abstract*: Sleep is considered as completely obligatory element for an individual's welfare and is an essential element for the overall physical and mental well-being of a person. Sleep can be contemplated as a virtual detachment of an individual from his surroundings. Normal human spent 30% of their life-time in sleep. Sleep scoring system and its stages when properly examined can give clinical information regarding diagnostic patients with sleep disorders. Since, manual sleep stage classification is a tedious process that takes a lot of time by sleep experts performing data analysis on this field. Moreover errors and variability's between classifications of same data are recurrent. Due to this, there is a great need of automatic categorization system to support reliable classification. Sleep scoring is under taken by the examination and visual inspection of PSG (polysomnograms) done by sleep specialist. PSG is specialty test, the conduction of which includes the recording of various physiological signals. Automatic schemes based on Electromyography signals analysis are discussed in order to understand the problem associated with sleep scoring and its stages. Electromyography is an electro diagnostic medicine technique for evaluating and recording of the electrical activity produced by skeletal muscles. EMG is performed using an instrument called electromyograph to produce record called electromyogram. The signals obtained are processed using digital processing tools so as to extract information. Soft computing technique ANN (Artificial Neural Network) are used to analyze the signals. ANN or connectionist systems are computing systems inspired by the biological neural networks that constitute animal brains. Using ANN for automatic sleep scoring is especially promising because of new ANN learning algorithms allowing faster classification without decreasing the performance. Both appropriate preparations of training data as well as selection of the ANN model make it possible to perform effective and correct recognizing of relevant sleep stages. Such an approach is highly topical, taking into consideration the fact that there is no automatic scorer utilizing ANN technology available at present. The high performances observed with systems based on neural networks highlight that these tools may be act new tools in the field of sleep research. In this scenario we are surmised the review regarding the computer assisted automatic scoring of sleep using Electromyophy signals and soft computing technique ANN.**

***Keywords*: Automatic Sleep scoring system, Sleep Stages, Electromyography Signals, Polysomnograms (PSG), ANN (Artificial Neural Network)**

1. Introduction

A. Sleep and sleep scoring

Sleep is an essential element for an individual's well-being and is considered important for the overall physical and mental health of a person. Sleep is a state in which the physical and mental functions of an individual are in a state of halt, as well as various external actions do not affect the person which is in the resting state [1]. Thus, sleep can be considered as a virtual detachment of a person from his surroundings. In normal humans, about 30% of their life-time is spent for sleep. The concept of sleep is considered to be highly mysterious and a topic of discussion and research interest since ages and it has engrossed the researchers all over the world [2]. Prolonged sleep disorders or a continuing sleep insufficiency invites various diseases of heart, kidney, etc and increases the risk of long term passive diseases like diabetes, high blood pressure as well as stroke in extreme cases. These are a source of tenderness and anguish to the individual experiencing them such as insomnia, sleep walking, narcolepsy and nocturnal breathing disorders and hence, they need to be treated [3]. Sleep scoring is an important aspect in the field of sleep medicine as well as sleep research. Classically, for years together, sleep scoring has been under taken by the examination and visual inspection of polysomnograms (PSG) done by a sleep specialist [4]. Here, PSG is specialty test, the conduction of which includes the recording of various physiological signals like Electrooculararogram (EOG): the records of eye movements both for left and right eyes, Electroencephalograph (EEG): a measure of well-known brain waves generated by cortex and other integrative processing mechanism, Electromyogram (EMG): the record of electrical activity that emanates from active muscles. All of these signals when recorded for a short period of time called epoch and analyzed indicate different stages of sleep [5].

B. Sleep scoring system

Sleep scoring system is a rule-based neurophysiologic characterization requiring an understanding of the basic mechanisms underlying the generation of cephalic electric potentials coupled with muscle signals and eye movement.

Signals of interest are generated from the brain cortex, facial muscles as examined by the sub mental EMG, and eye movement as detected by the EOG [6]. Interference with the signals of interest is encountered through many mechanisms, including physiological attenuation of the cerebral electric potentials by scalp muscle and bone, intrusion into the signal by slow cyclic respiration, movement, ECG signal, external electric fields, and impaired contacts between the recording electrodes and the skin surface. Discriminating true signal from artifact can be one of the most challenging aspects of scoring stages of sleep [7].

C. *Sleep stage classification*

The Rechtschaffen and Kales manual for normal sleep classifies the epochs and scores them as waking, Rapid Eye Movement (REM), Non-Rapid Eye Movement (NREM) as the basic three stages of sleep. Further, there is a classification provided NREM four stages of sleep. These stages are scored according to the various signals recorded in that particular epoch [8]. The various stages of sleep described by Rechtshaffen and Kales manual for normal sleep are defined as follows [9]:

- Stage 0: This stage is termed as the wakeful stage and is the condition of an individual when he/she prepares to sleep. Here, the body is at rest and in a relaxed state with eyes closed and the EMG of the subject may be high or in a moderate range dependent upon the muscle tension.
- Stage 1: This stage comes after some time is elapsed in stage 0 and the EMG of the subject would be lower value as compared to the previous stage.
- Stage 2: This is the progression of the subject into the condition of sleep and the EMG value further decreases as compared to the previous stages on account of reduced muscle tension.
- Stage 3: The EMG in this stage reduces due to relaxed muscles rapid eye movements are negligible in this case.
- Stage 4: This stage records a moderate EMG value and the subject may be termed asleep.

REM Stage: In this stage, the EMG demonstrates muscle tones which may be called as Twitches or the occasional short tons of distal muscle along with transient activities which might have arisen from blood pressure or from the heart beating frequency [10].

D. *Electromyogaphy signals (EMG)*

Any biomedical signal is a collective of electrical signals given out by any organ and is considered as a representative of some specific physical variable of having research interest. These biomedical signals like any electrical signal can be represented as a function of time having essential attributes like amplitude, phase, and frequency [11]. EMG signals are unique biomedical electrical signals which manifest out of the activity of the neuroskeletal muscles. They have been widely employed for the purpose of electro diagnostic medicine. This particular technique can be employed with the help of an instrument called an electromyography there by yielding a record known as an electromyogram. Proper analysis of the EMG signals help in the diagnostic procedures undertaken to assess the health of a motor nerves and the activities controlled by them [12]. EMG signals are unique biomedical electrical signals which manifest out of the activity of the neuron-skeletal muscles like contraction, relaxation, etc. [13]. Bearing the fact in mind that all the contraction and relaxation activities of various muscles and organs are controlled by the central nervous system, it can be concluded that the EMG signals which is complex manifestation is a function of the nervous system which fully controls it and these signals are further dependent on various other properties of muscles like their anatomy and physiology [14]. The smallest functional unit to describe the neural control of the muscular contraction process is called a Motor Unit [15]. It is defined as the cell body and dendrites of a motor neuron, the multiple branches of its axon, and the muscle fibers that innervates it. The term units encloses the behavior that all muscles fibers of a given motor unit act as one within the innervations process. This is shown in Fig.1.1 (a). An EMG signal is the train of Motor Unit Action Potential (MUAP) showing the muscle response to neural stimulation. The process of acquiring EMG signal and the decomposition to achieve the MUAP has been shown in Fig. 1

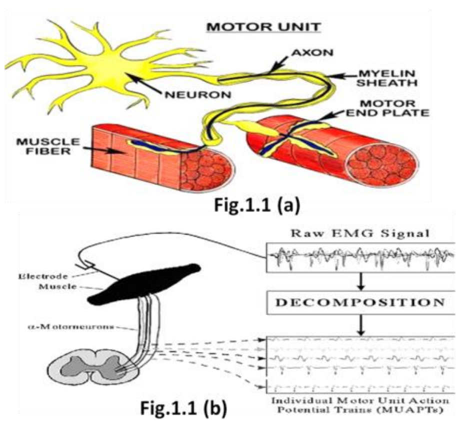

Fig. 1. Presentation of Motor Unit and Motor Unit Action Potential

In their course of travel through organs and tissues, the EMG signals get encountered with noise. Usually, the EMG signals are detected by an EMG detector which is isolated particularly on the surface of the skin [16]. This EMG detector thus collects signals which originates from different motor units and could be a result of interaction of different signals which are generated at that particular time. Thus, the detection of EMG signals must be undertaken with powerful, sophisticated and advance methods when they are required for medical diagnostic purposes. The EMG signals which are collected from muscles involve sophisticated methods for the purpose of detection, noise, decomposition and reduction, analyses and processing, as well as classification [17].

E. ANN (Artificial Neural Network)

ANN is a widely engaged soft computing technique. They have been used for a variety of purposes like pattern and image recognition, analysis, classification, along with functional monitoring in fields concerned with signals and systems. Its robustness and flexibility has made it popular for computing in a wide array of fields [18]. The optimum balancing of equation of designing ease, time of execution and the level of accuracy has made it a highly used classifier when large amount of computing is required [19]. The fundamental design and modeling of (NN) neural networks is inspired from the biological neural systems. Usually in the neural networks designed for such computations are much simpler structures and possess the abilities of learning and reacting [20]. The primary features of neural networks which are adopted for computational purpose are its ability to adapt as well as its characteristic of non-algorithm and parallel-distributed memory [21]. A standard feed forward neural network consists of three layers of operation viz. input layer, hidden layer, output layer. There can be one or more hidden layers which perform an array of different functions. The hidden layers are made up of cells which undertake the function of summing up the output which is a product of preceding layer [22]. This summing is done after multiplying it by weight vector through neurons, Hence, each cell or anode gives a resultant output with the given input according to a non-linear transfer function which is known as the activation function [23].

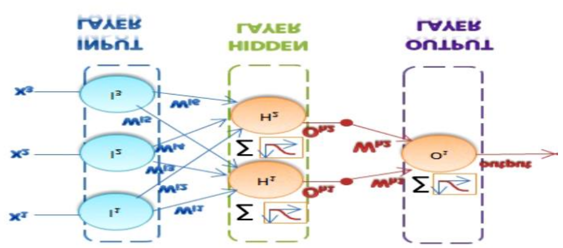

Fig. 2. Layers

The determination of number of hidden layers is the critical task when adopting and designing the artificial neural network. It is unknown at the starting of the process unlike the input and the output layer which have a precise definition from the beginning. Hence, the input is fed and the output is observed by the neural network [24]. With numerous such iterations, and by employing the trial and error method, the number of hidden layers and their activation functions are calculated gradually by the artificial neural network. This process is called the training phase of the artificial neural network which may be time consuming [25]. The artificial neural network must be trained to function as per requirement of the computation at hand. Usually an artificial neural network is expected to have a number of hidden nodes because the one possessing a smaller number of nodes comes with the constrained capability of distinguishing between complex patterns [26].

F. ANN technology

ANN's are computational tools composed of a large number of highly interconnected elementary processors (also named as cells or neurons). Information is stored in each processor as intensities (also named weights) of its connections [27]. The basic idea of connectionism is that global coherent behavior can emerge from such organization. Though a wide variety of ANN's models exist, each can be completely defined by three characteristics:

- *The topology of the network:* This characteristic relates to the network organization. Data are generally presented to the network through a set of input cells. After a processing phase, the result is available through a set of cells referred to as output cells [28]. These cells interact with the external world but other cells with no direct interaction with the external world can exist (they are referred to as hidden cells). Each connection is characterized by its intensity (weight) and by the direction of propagation of the information. An individual network is characterized by the numbers of cells and the connections between the cells. The most employed model is the multilayer perceptron wherein cells are set in successive layers [29]. The input layer is separated from the output layer by one (or more) hidden layer(s). Each layer is generally fully connected to its adjacent layer, information being processed from the input layer to the output layer [30].
- *The transfer function of each cell:* Each cell sums up the weighted inputs it receives from other cells and generates an output value (also referred to as the state of the cell) using a transfer function. This transfer function is usually a sigmoid or a binary function with the output value generally evolving between two limits (-1 and +1 or 0 and +1) [31].
- *The learning rule:* To process data properly, the intensity of each connection is adjusted during a training phase which orients the global behavior of the network toward the one expected by the operator. The learning rules applied during the training phase can be divided into two main classes; supervised and unsupervised learning rules [32]. The unsupervised learning procedures strive to catch regularities in the input data. The supervised learning procedures require external intervention (performed by a 'teacher') to guide the training phase. The principle of supervised learning is to provide the network with a set of reference 'patterns' with which adequate weights are computed. With the multilayer perceptron, the most frequently employed learning rule is the back propagation algorithm described by Rumelhart et al. (1986) [33].This algorithm is based on the presentation by a teacher, to the network, of vectors (an input vector and the expected output vector). Information from the input layer is thus propagated

down through the network to the output layer. After propagation, the quadratic error computed from the observed and expected outputs is used to modify the value of each weight in the network [34]. When the learning phase is ended, the network is supposed to associate any input vector with an appropriate output vector. Further details concerning artificial neural network computation can be found in Leuthausser, Freeman and Skapura [35], [36].

2. Historic overview

Krausman et al. [37] used method and an apparatus which were disclosed for scoring the quality of sleep experienced for a specific period. This sleep monitoring apparatus includes a motion server that quantifies the temporal variation in the subject's motion, an analog to digital converter to sample the sensor data, a microprocessor with embedded programmable memory to store control and processing firmware [38]. The firmware for this apparatus directs the microprocessor to a sample space sensor output directs the microprocessor to analyze temporarily stored data to compute a sleep score, controls the operation of display means. A high score indicates restful sleep (very low movements) while a low score indicates excessive restlessness during monitored sleep period. Park et al. [39] proposed an automated method for sleep stage scoring using hybrid rule and case based reasoning. The method comprised of signal processing unit, rule based scoring unit and case based scoring unit. Authors applied this methodology to three recordings of normal sleep and three recordings of obstructive sleep apnea (OSA). Average agreement rate in normal recording was 87.5% and case based scoring showed agreement rate by 5.6% [40]. This showed several advantages in sleep scoring: high performance on sleep disorder recordings and learning ability. Silber et al. [41] have discussed the work of AASM visual scoring task force behind the new rules. Reliability studies of R and K scoring were reviewed; reliability was low for stage 1 and moderate for slow wave sleep.

Moser et al. [42] investigated differences between visual sleep scoring according to classification developed by Rechtschaffen and Kales (R and K) and scoring based on AASM (American Academy of Sleep Scoring). All night polysomnographic recording were scored visually according to R and K rules and AASM rules by experienced sleep scorers. Healthy subjects (38 females and 34 males) aged between 21 and 86 years were taken. While sleep latency, total sleep time, sleep efficiency were not affected by classification standard, time spent in sleep stage 1(S1/N1), stage 2(S2/N2) and slow wave sleep (S3+S4/N3) differed significantly between R and K and AASM classification [43]. Tagluk et al. [44] classified an alternate system which estimates sleep stages of human being through a multi-layer neural network that simultaneously employs EEG, EMG, EOG. The data was recorded through polysomnography device for 7 hours for each subject. A good scoring was attained through trained ANN. Linssen et al. [45] have used the inter and intra individual variability of the frequency power density spectral and the surface EMG signals. Surface EMG amplitude parameters and the muscle fiber conduction velocity (MFCV) was studied in 26 healthy volunteers during fatiguing isometric ischemic intermittent exercise of the biceps brachii at 80% of the maximal voluntary contraction level, with a contraction rate of 30/min. No significant age effects were found. Males were significantly stronger. Mambrito et al. [46] discussed a system for acquiring, processing and decomposing EMG signals for the purpose of extracting as many motor unit action potential (MUAP) with greatest level of accuracy. The system consisted of four sections. The first section employs signal acquisition and quality verification. The second section includes signal sampling and conditioning. The third section consists of signal decomposition technique. Thus, from these three sections motor unit action potential trains were extracted from EMG signal using highly computer assisted algorithm. It was showed that performance of system has consistency and accuracy [47].

Raez et al. [48] have used EMG signal for biomedical applications. EMG signals acquired from muscles require advanced method for detection, decomposition, processing and classification. Authors illustrated various algorithms for EMG signal analysis to provide efficient and effective ways of understanding the signal and its nature. The researchers provided a good understanding of EMG signal and its analysis procedure. Krausman et al. [49] used method and an apparatus which were disclosed for scoring the quality of sleep experienced for a specific period. This sleep monitoring apparatus includes a motion server that quantifies the temporal variation in the subject's motion, an analog to digital converter to sample the sensor data, a microprocessor with embedded programmable memory to store control and processing firmware. The firmware for this apparatus directs the microprocessor to a sample space sensor output directs the microprocessor to analyze temporarily stored data to compute a sleep score, controls the operation of display means. A high score indicates restful sleep (very low movements) while a low score indicates excessive restlessness during monitored sleep period [50]. Park et al. [51] proposed an automated method for sleep stage scoring using hybrid rule and case based reasoning. The method comprised of signal processing unit, rule based scoring unit and case based scoring unit. Authors applied this methodology to three recordings of normal sleep and three recordings of obstructive sleep apnea (OSA). Average agreement rate in normal recording was 87.5% and case based scoring showed agreement rate by 5.6%. This showed several advantage in sleep scoring: high performance on sleep disorder recordings and learning ability. Silber et al. [52] have discussed the work of AASM visual scoring task force behind the new rules. Reliability studies of R and K scoring were reviewed; reliability was low for stage 1 and moderate for slow wave sleep. Moser et al. [53] investigated differences between visual sleep scoring according to classification developed by

Rechtschaffen and Kales (R and K) and scoring based on AASM (American Academy of Sleep Scoring) [54,55]. All night polysomnographic recording were scored visually according to R and K rules and AASM rules by experienced sleep scorers. Healthy subjects (38 females and 34 males) aged between 21 and 86 years were taken. While sleep latency, total sleep time, sleep efficiency were not affected by classification standard, time spent in sleep stage 1(S1/N1), stage 2(S2/N2) and slow wave sleep (S3+S4/N3) differed significantly between R and K and AASM classification.

Ming Ming Liu et al. [56] identified that EMG signals for dynamically contracting muscle have never been used to predict experimentally known muscle force across subjects. Authors used an Artificial Neural Network (ANN) approach to first derive an EMG-force relationship from a subset of experimentally determined EMGs and muscle forces; second, used this relationship to predict individual muscle forces for different contractile conditions and in subjects whose EMG and force data were not used in the derivation of EMG-force relationship; and third validated the predicted muscle forces against the known forces recorded in vivo. Considering the conceptual differences in the tasks investigated (e.g. slow walking vs. trotting), the intra-subject results obtained were superior to those published previously. The inter-subject results typically gave cross-correlation coefficients between actual and predicted forces of >0.90 and root mean square errors of <15%. Subasi et al. have used an accurate and computational efficient means of classifying EMG signal patterns. In this study, authors used feed forward error back propagation artificial neural network (FFBANN) and wavelet neural network (WNN) based classifiers for comprising their accuracy in classification of EMG signals. The success rate for WNN technique was 90.7% and for FFEBANN technique 88% [57]. Wang et al. determined muscle activations from EMG signals by using neural network. The feed-forward neural network model of muscle activation is composed of four layers. Thus, an adjusted back-propagation algorithm was developed. Once muscle activations were obtained and hence used to estimate muscle force. The result obtained showed that this neural network model can be used to represent relationship between EMG signal and joint movements [58].

A. Measurement of electromyography signals

EMG Signals fluctuates with time and can be utilized to control machines and frameworks. EMG signals is the electrical movement created amid the compression of a skeletal muscle. EMG measures muscle reaction or electrical action in light of a nerve's incitement of the muscle [59]. Amid the estimation, one or all the more little needles (additionally called obtrusive anodes) are embedded through the skin into the muscle. The electrical action got by the anodes is then shown on an oscilloscope (a screen that shows electrical action as waves). EMG signals can likewise be taken by noninvasive anodes. EMG measured by non-obtrusive terminals is called surface EMG signals [60]. A pictorial perspective of the EMG signal has been demonstrated in the Fig. 2. After a terminal has been embedded, patient may be requested that agreement the muscle, for instance, by lifting or twisting his hand. The activity potential (size and state of the signal) that this makes on the oscilloscope gives data about the capacity of the muscle to react when the nerves are invigorated. As the muscle is contracted all the more compellingly, more muscle filaments are actuated creating activity possibilities.

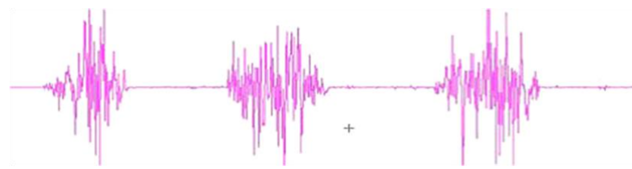

Fig. 3. Representation of EMG Signal

The EMG signal shown in the Fig.1.2 obviously demonstrates that EMG signal is a non-stationary signal. Genuine EMG signal is extremely powerless and is exceptionally delicate to commotion. It is likewise of low adequacy. The estimation of EMG signals must be done precisely to keep it away from twisting and lapses [61].

B. Applications of EMG signals

EMG signals are extensively utilized in applications such as controlling dynamic prosthesis, wheelchairs, exoskeleton robots, restoration, quiet discourse acknowledgment, and controlling computer games as it can be measured on a human skin surface with non-intrusive electrodes [62]. In monetarily accessible prosthetic gadgets EMG signals have been misused for a corresponding control method in which the abundance of the engine voltage or its rate and power fluctuate in direct extent to their amplitude. To enhance usage, a control technique in light of the characterization of EMG signals has been broadly concentrated. In such a system, a classifier is developed for the surface EMG signals to perceive the proposed human developments utilizing ordered developments. The EMG signal is likewise used to help in distinguishing neuromuscular variations from the norm [63].

C. Application of artificial neural network (ANN)

The system which estimates sleep stages of human befitting through a multi-layer neural network (NN) that simultaneously employs EEG, EMG and EOG. The data were recorded through polisomnography device. These collective variant data were first grouped by an expert physician and the software of polisomnography, and then used for training and testing the proposed Artificial Neural Network (ANN). A good scoring was attained through the trained ANN, so it may be put into use in clinics where lacks of specialist physicians.

D. Other application

Having their ability to reproduce and model nonlinear processes, ANNs have found uncountable applications to a wide range of disciplines.

- Application areas include system identification and control (vehicle control, trajectory prediction, process control, natural resources management), quantum chemistry, game playing and decision making (chess, poker), pattern recognition (radar systems, face identification, signal classification, object recognition and more), sequence recognition (gesture, speech, handwritten text recognition), medical diagnosis, finance (e.g. automated trading systems), data mining, visualization, machine translation, social network filtering and e-mail spam filtering.

- ANN's have been used to diagnose cancers, including lung cancer, prostate cancer, and colorectal cancer and to distinguish highly invasive cancer cell lines from less invasive lines using only cell shape information.
- ANNs have been used for building black-box models in geosciences: hydrology, ocean modeling and coastal engineering, and geomorphology are just few examples of this kind.

E. Uses of electromyography signals in sleep stages

The EMG signals are muscle twitch potentials that may offer additional assistance in defining a sleep stage. Their use is based on the finding that muscle activity decreases during sleep, with muscle activity at its nadir during REM sleep [64]. In many cases, however, appreciating a decreasing muscle tone can be difficult and the relative silence during REM sleep may not be of help in distinguishing it from the preceding or subsequent sleep stages. Compounding the problem of interpreting EMG channels is intrusion of artifact into the signal. Some examples include cyclic jaw movements, teeth grinding (bruxism), or steady high-amplitude noise generated by increased pressure on an electrode (eg. as caused by lying on the chin) [65]. Additionally, muscle artifact spilling over into cortical leads is not an unusual finding. ECG signal is a specific type of cardiac artifact that can appear in all or several channels and can be recognized by tracking the repeating QRS complex throughout the other leads. Recommended EMG technical requirements include 3 chin EMG electrodes, 2 of which are used throughout the study with an additional lead as a backup [66].

F. Uses of artificial neural network (ANN)

- In learning algorithm, as any algorithm will work well with the correct hyper parameters for training on a particular data set. However, selecting and tuning an algorithm for training on unseen data requires significant experimentation.
- If the model, cost function and learning algorithm are selected appropriately, the resulting ANN can become robust.
- It is used as function approximation, or regression analysis including time series prediction, fitness approximation and modeling.
- It can be used as a classifier which involves the pattern and sequence recognition.
- ANN has found capabilities in data processing which includes filtering, clustering, blind source separation and compression.

3. Conclusion

The research would result in an effective system for computer assisted automatic sleep scoring system and its classification using EMG signals which would employ artificial neural network for its functioning. Electromyography signals (EMG) are very versatile and can be used for various other purposes like feature extraction, hand gesture recognition, etc. which can be researched in future. EMG signals are unique electrical signals which manifest out of the activity of the neuro-skeletal muscles. They have been widely employed for the purpose of electro diagnostic medicine. The data collected for the analysis would be the set of the signals obtained from the patient's body. These electrical signals can be collected with the help of polysomnograph (PSG) from a sleep laboratory or clinic in the vicinity of researcher and to which the researcher has accessibility. Once the data collected, it would be applied to the classifier that is ANN for its classification. Although, the ANN is a highly research topic, the utilization of the same for biomedical purpose of sleep scoring is novel when employed with electrical signals acquired from body. The novel technique of sleep scoring could be of greater significance in various applications for neurological clinics, and particularly helping the neurologist in their purpose of the wake and sleep correlates as well as in the diagnosis of certain sleep disorders.

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