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Portable Real-time Support-Vector-Machine-Based Automated Diagnosis and Detection Device of Narcolepsy Episodes

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Abstract – **Individuals with certain sleep disorders (e.g. narcolepsy) are subject to uncontrollable sleep episodes accompanied by cataplexy and thus these patients are more vulnerable to household and occupational accidents. Currently, narcolepsy has no cure, and this research pursues developing a portable medical device to assist in narcolepsy treatment through providing diagnosis, real-time detection and logging of narcolepsy episodes.**

I. Introduction

Narcolepsy is a form of sleep disorders characterized by uncontrollable recurring episodes of excessive daytime sleepiness (EDS). An episode can last for a few minutes up to an hour, and is accompanied by rapid eye movement sleep (REM); other narcolepsy symptoms are also listed in [1-2]. Not only these symptoms prevent an individual from practicing normal and productive life efficiently, but also make the narcolepsy patient more liable to risks of accidents during daily chores and activities. An undiagnosed patient will eventually suffer social, educational, financial difficulties [2-11] as well as depression [9].

Automated sleep monitoring and classification techniques are being developed to improve diagnostic and therapeutic procedures for individuals suffering from sleep disorders. There is no present cure for narcolepsy [10], but behavioral and medical therapies can be used to control some symptoms. Treating sleep disorders requires real-time monitoring and analysis of sleep states [3] [13]. The conventional sleep classification process uses manual visual scoring of a polysomnogram which consists of 8 electroencephalogram (EEG) channels (O1, O2, T3, T4, C3, C4, Fpl, and Fp2 based on the 10-20 electrode placement system), one electro-oculogram (EOG) channel, and a single electromyogram (EMG) [13-14]. The EEG represents the evoked potentials generated due to encephalon activities which indicates cerebrum awakening and sleep depth [16]. The EMG records the electrical activity of the muscles which decreases during sleep, and finally, the EOG represents the electrical activity caused by eyeball movement.

The risks imposed on narcoleptic individuals and the inconvenient clinical diagnosis procedures motivated the need for developing and improving the diagnosis and detection procedures. A portable implementation of the diagnosis techniques will unburden the patient from the inconvenient time-consuming clinical recording sessions in an unfamiliar environment which can adversely influence the diagnostic utility of the tests [2]. Achieving portability requires the reduction of the number recorded signals which will also simplify the sleep recording and classification procedures.

The focus of this research activity is developing a portable device to assist in the treatment of narcolepsy patients through providing real-time monitoring and detection of narcolepsy episodes. Several sleep classification and staging algorithms were investigated and developed in MIAMI group, University of Waterloo in collaboration with the Division of Respirology, Schulich School of Medicine and Dentistry at the University of Western Ontario [2]. The performance of different sleep classification algorithms is evaluated according to the classifier accuracy. Furthermore, the algorithms need to be optimized to minimize execution time and code size in order to run efficiently on low power portable processing platforms with limited resources.

This paper introduces a prototype of a portable medical assistive device that executes a high accuracy (96%) real-time narcolepsy detection algorithm based on support-vector-machine classifier. The device also logs the narcolepsy episodes to provide objective data to the treating physician that is required for improving the medical treatment and drug administration.

II. Narcolepsy Detection

A. Narcolepsy Diagnosis and Sleep Staging

Narcolepsy symptoms are common with several other disorders; therefore they cannot exclusively be used to diagnose narcolepsy. The detection of sleep episodes is based on sleep staging and classification information elicited from the EEG spectrum. In the case of a normal sleep, the EEG spectrum starts with a sequence of four Non-rapid Eye Movement (NREM) stages followed by rapid eye movement (REM) sleep which is deep and accompanied by dreaming. The first four stages (NREM sleep) progress from short light to deeper episodes. At the end of stage 4, REM sleep commences and a typical eight-hour sleep encompasses four or five sleep cycles following the same pattern. On the other hand, a narcoleptic spectrum would exhibit the

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occurrence of REM sleep stage right after falling asleep (stage 1), rather than being the last stage of the sleep cycle. This characteristic is adopted for developing the automated narcolepsy detection algorithms [2].

B. Feature extraction and Automated Sleep Classification

Feature extraction algorithm elicits four features from the EEG signal, each representing a frequency band within the EEG spectrum: delta (0-4Hz), theta (4-8Hz), alpha (8-12Hz) and beta (12-16Hz). Samples are grouped into epochs of 30 seconds, and each epoch is processed separately to extract its features. A sample EEG recording for 60 epochs is shown in Fig. 1 and the corresponding values of the extracted features are plotted in Fig. 2. The feature extraction algorithm is based on Daubechies-2 wavelet transformation with four resolution levels to provide the required features. Wavelet transform provides information in both short and long sampling time intervals and thus taking transient information in consideration, unlike Fast Fourier transform (FFT) which estimates the average of the signal while discarding transients [2].

Several sleep staging algorithms based on different classification techniques including: Learning Vector Quantization (LVQ), Probabilistic Neural Network (PNN) and Feed-forward Neural Network (FF-NN) were evaluated and discussed in [2]. The SVM-based classifier implemented in the prototype presented in this paper provided the highest classification accuracy of 96%.

C. Support Vector Machine (SVM)

Support vector machine (Fig. 3) is a binary classification algorithm. Given a set of training data points labeled as positive or negative (belonging or not belonging to a class), it searches for two parallel hyper planes with maximum separation (margin) between members of the two sets. The decision boundary between the two classes is the parallel plane bisecting the margin. After this training phase, each new data point is classified according to its position relative to the decision boundary in the testing phase. The SVM used in the prototype is based on the Newton-SVM which is capable of handling a large training dataset accurately producing a decision boundary in a short processing time [17].

D. Validation

The classification accuracy of the SVM based classifier was evaluated by applying Jack-Knifing cross validation statistical technique. This iterative process recruits one data sample at a time for testing which makes it suitable for limited data problems. The classifier is tested with 60 epochs of data that were manually scored by a physician yielding an accuracy of 96%. The same test was applied on different classifiers in [2] and SVM proves to achieve the highest classification accuracy as shown in Table I.

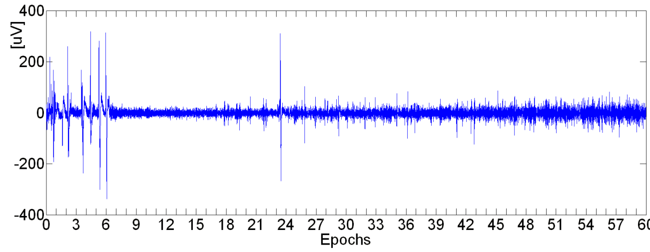

Fig. 1. EEG spectrum for 60 epochs (1800 seconds)

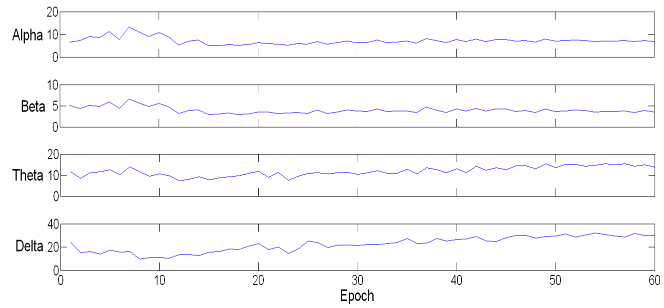

Fig. 2. Values of the Alpha, Beta, Theta and Delta frequency components for the 60 epochs

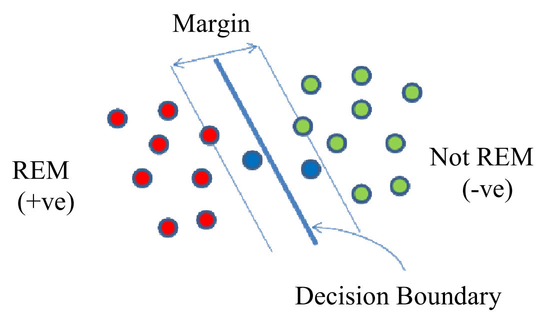

Fig. 3. Support vector machine

TABLE I
CLASSIFICATION SUMMARY

Classifier	Classification Accuracy
LVQ	70%
PNN	79%
FF-NN	85%
SVM	96%

III. PORTABLE NARCOLEPSY ASSISTIVE DEVICE

A. Problem Formulation and Proposed Solution

As mentioned previously, narcoleptic individuals are more prone to occupational and household accidents, imposed by the symptoms that accompany narcolepsy episodes. The proposed prototype is a portable device that monitors the

EEG spectrum in real-time and executes sleep narcolepsy detection algorithms. This device has the potential to secure the safety of the patient while practicing daily chores, through alerting the patient and companions by an audible alarm when a narcolepsy episode is imminent. Moreover, the device serves as a data logger recording the occurrence of the episodes to provide objective information for the treating physician.

B. Device Hardware

The prototype is optimized to achieve satisfactory performance while maintaining low power consumption. The AR-B1831 single-board-computer (Accroser Technology Co. Ltd., Cypress, California) with an Intel Pentium-M processor (Fig. 4) is chosen for prototyping. This system satisfies the computational power required for executing the algorithms which was challenging for previous prototypes. It also supports ACPI (Advanced Configuration and Power Interface) allowing further reduction of power consumption. The device board measures 16 cm x 12 cm, and an onboard flash memory stores the operating system and developed application.

The block diagram in Fig. 5 shows the main hardware components; differential EEG recording of C3-A2 channels provides the EEG source signal which is filtered and amplified using in-house high gain amplifier and fed in to the analogue input of the SBC. The system also houses an alarm buzzer to issue an audible alert when a narcolepsy episode is detected. Additional peripherals were added to facilitate the device usage by the physician. The PC interface allows training the device using previously recorded manually scored sessions. Also, it allows downloading the narcolepsy episodes log.

C. Device Software

The software running on the device exploits available hardware resources and peripherals for data acquisition, feature extraction and execution of the developed narcolepsy detection algorithm. Also it handles the PC and patient interfaces for providing access to the physician (training and downloading logs) and issuing alarms when necessary. The software operates in two modes: Training and Testing as shown in Fig. 6.

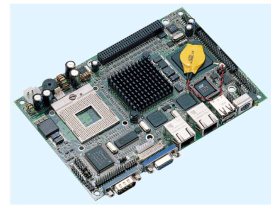

Fig. 4. Single board computer board

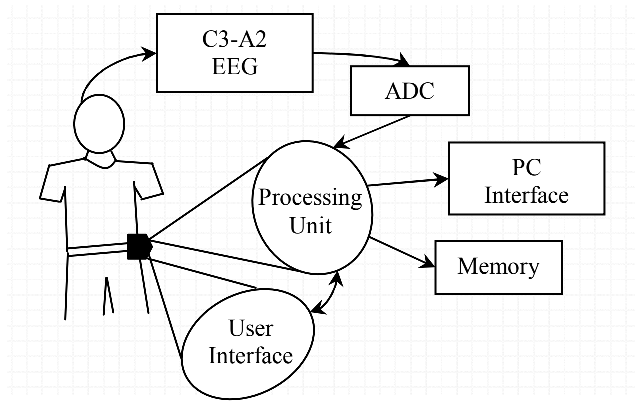

Fig. 5. System block diagram

Training Mode

This mode is activated when the device is connected to a PC. In training mode the physician is allowed to send the EEG samples captured during a recording session grouped in epochs of thirty seconds. Each epoch is associated with a manually scored label identifying its sleep stage. The device receives each epoch and applies the feature extraction

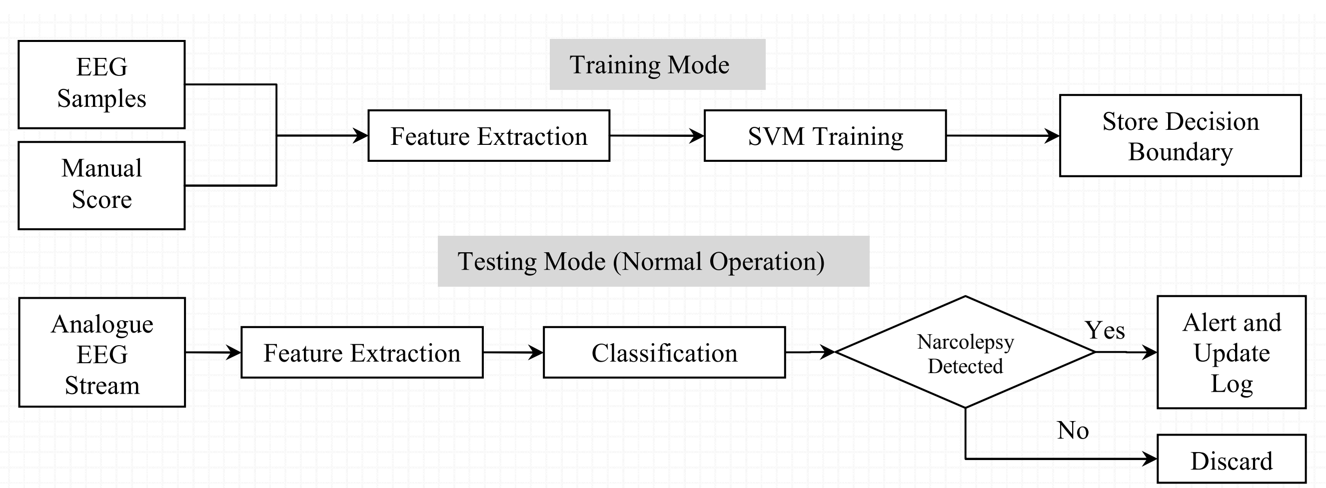

Fig. 6. Software modes of operation

technique discussed in section B. With all features and labels ready, the SVM training algorithm is invoked and a decision boundary is constructed. The boundary is stored and then the device is ready to run in testing mode.

Testing Mode

As for the testing mode, it is activated after decision boundary is saved and the device is disconnected from the PC. The device uses the analogue input channel to receive EEG stream which is then divided into thirty seconds epochs. Each epoch is processed individually to extract the features which are then passed to the sleep classifier to detect narcolepsy episodes. In case of a positively detecting an episode an audible alarm is issued and the narcolepsy episodes log is updated. The log is downloadable when the physician reconnects to the device.

IV. CONCLUSION

In this paper a portable real-time narcolepsy detection device prototype was introduced. This prototype can be used for diagnosis and assist in therapeutic procedures. The detection algorithm employs a support vector machine (SVM) classifier which exhibited the highest classification accuracy (96%) compared to other techniques previously developed. The device responds to the occurrence of narcolepsy episodes by alerting the patient and logging the event time.

REFERENCES

[2] S. R. I. Gabran, S. Zhang, M. M. A. Salama, R. R. Mansour, C. George, “Real-time automated neural-network sleep classifier using single channel EEG recording for detection of narcolepsy episodes”, 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society EMBC, pp: 1136-1139, 2008.

[3] R. Broughton, Q. Ghanem, Y. Hishikawa, Y. Sugita, S. Nevsimalova, B. Roth, “Life effects of narcolepsy: relationships to geographic origin (North American, Asian or European) and to other patient and illness variable”, The Canadian Journal of Neurological Sciences, vol. 10, pp: 100-104, 1983.

[4] W. A. Broughton and R. J. Broughton, “Psychosocial Impact of Narcolepsy”, Sleep, vol. 17, pp: S45-49, 1994.

[5] C. Hublin, M. Partinen, J. Kaprio, M. Koskenvuo, C. Guilleminault, “Epidemiology of narcolepsy”, Sleep, vol. 17, pp: S7-12, 1994.

[6] Q. Ma, X. Ning, J. Wang, J. Li, “Sleep-stage Characterization by Nonlinear EEG Analysis using Wavelet-based Multifractal Formalism”, 27th Annual International Conference of the Engineering in Medicine and Biology Society EMBC, vol. 1, Issue 4, pp: 4526-4529, 2005.

[7] P. Passouant, and M. Billiard, “The evolution of narcolepsy with age,” Narcolepsy: Advances in sleep research, vol. 3, C. Guilleminault, W. C. Dement, P. Passouant, (Eds), Spectrum Publications, New York, pp: 179-196, 1976.

[8] National Institute of Neurological Disorders and Strokes: www.ninds.nih.gov/disorders/narcolepsy/narcolepsy.htm

[9] J. M. Fry, “Treatment Modalities for Narcolepsy”, Neurology, vol. 50, Suppl. 1, pp: S43-48, 1998.

[10] D. Bruck, “The Impact of Narcolepsy on Psychological Health and Role Behaviors: Negative Effects and Comparisons with Other Illness Groups”, Sleep Medicine, vol. 2, pp: 437-446, 2001.

[11] K. M. Beusterien, A. E. Rogers, J. A. Walsleben, H. A. Emsellem, J. A. Reblando, L. Wang, M. Goswami, B. Steinwald, “Health-Related Quality of Life Effects of Modafinil for Treatment of Narcolepsy”, Sleep, vol. 6, pp: 757-765, 1999.

[12] H. Kellerman, “Sleep Disorders: Insomnia and Narcolepsy”, Brunner/Mazel Inc., New York, 1981.

[13] S. R. I. Gabran, Shuo Zhang, E. F. El-Saadany, M. M. A. Salama, “Narcolepsy assistive device”, European Conference on Emergent Aspects in Clinical Data Analysis EACDA, 2005.

[14] L. Huang, Q. Sun, J. Cheng, “Novel method of fast automated discrimination of sleep stages”, Proceedings of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, vol. 3, pp: 2273- 2276, 2003.

[15] L. Jianping, “EEG Characteristic Extraction in Different Brain Activity and Sleep Quality Estimation”, Ph.D. thesis, Xi'an Jiaotong University, 1997.

[16] V. Bezruk, “Automated Recognition of Sleep Stages by Electroencephalograms”, 9th International Conference - The Experience of Designing and Applications of CAD Systems in Microelectronics, pp: 58, 2007.

[17] G. Fung and O. L. Mangasarian, "Finite Newton Method for Lagrangian Support Vector Machine Classification", Data Mining Institute, Computer Sciences Department, University of Wisconsin, 2002.