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Fatigue Detection Using Voice Analysis: A Review

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ABSTRACT

Fatigue is harmful to human health as it impairs the maximal cognitive and physical performance. The main objective of this study is to estimate the level of fatigue in an individual by speech analysis. Non-intrusive fatigue measurement systems are required to accurately examine the attentiveness and concentration of a person prior to and in an ongoing critical mission or during life threatening activities (e.g. for pilots, drivers, neurosurgeons etc., fatigue is a critical element in their profession). Experimental results show that specific phonemes in human voice have certain dependence on fatigue. The speech based fatigue measurement system is non-intrusive and has many advantages over other measurements techniques. This paper discusses fatigue and how it affects the human speech, literature review, factors affecting acquisition and analysis of speech data, and the features examined by different researchers to estimate the level of fatigue by speech analysis.

***Keywords*:** Fatigue; Voice; Speech; Fatigue detection; Speech features.

1. INTRODUCTION

Fatigue is extreme tiredness that induces changes in psychological and physiological functioning. It is a state which reduces the efficiency and willingness to work. It is caused due to mental or physical exertion or illness. Causes of Fatigue are: (a) sleep deprivation, (b) intense physical activity, (c) prolonged mental activity, (d) prolonged durations of mental stress and anxiety, (e) poor sleep quality, and (f) health troubles. The affects of fatigue are: (a) lack of energy and motivation, (b) reduced cognitive ability, (c) weakened communicate skills, (d) reduced performance level, and (e) reduced level of alertness [1][2][3].

Fatigue is broadly classified as mental fatigue and physical fatigue. “Mental fatigue is a transient decrease in maximal cognitive performance resulting from strong or prolonged periods of cognitive activity” [4][5]. Numerous damaging chemicals are produced by the brain of a fatigued person, which blocks the nutrition channel. Consequently the neurons get suppressed and there is a decrease in flow of information and chaos occurs [6]. It is the temporary inability of a person to maintain optimal cognitive performance [7]. It depends upon the cognitive ability of an individual, and also upon other factors, such as sleep quantity, sleep quality and overall health. It is also seen that mental fatigue decreases physical performance [8]. This can be risky while performing tasks that require a certain level of focus, such as a doctor operating on a patient. “The Physical fatigue is the transient inability of a muscle to maintain optimal physical performance, and is made more severe by intense physical exercise” [9]. The mentally and physically fatigued state reduces the activity of central nervous system that adversely affects the cognitive information processing and attention level [10].

Fatigue state is dangerous to human well-being and can lead to fatal accident. Many existing techniques for detecting fatigue are: (a) Intrusive: Electrocardiogram (ECG) [11][12], Electroencephalogram (EEG) [1][13], Electromyogram (EMG) [2], Electro-oculogram (EOG) [2][12], Electro-magnetic articulography (EMA) [14], Electropalatography(EPG) [14], Ultrasound [14], Photoplethysmography(PPG) [12], Magnetic resonance imaging (MRI) [15], Galvanic skin response (GSR) [11], (b) Non-intrusive: Visual features (PERCLOS (Percent Eye Closure), eye blinking, yawning, head pose, facial expression etc.) [2][12], Speech features (Frequency, loudness, harmonic to noise ratio, cepstral coefficient, speech quality, formant etc.) [1][2], Reflexes Analysis (e.g. Key-striking, Gripping etc.) [16].

Advantages of speech based fatigue measurement over other measurement techniques are as follows: (a) utilization of already existing hardware and software, (b) un-obstructive, (c) free from sensors application and calibration efforts, (d) cost efficient, durable, and maintenance free, (e) even possible in darkness or where mobile devices cannot provide adequate visual feedback, (f) robust against different conditions of the environment and person-specific variations (e.g. luminous light, high humidity and temperature, wearing correction glasses, angle of face), and (g) advancement in technology enhances the speech recognition ability even in noisy environments.[2][16][17]

Speech sound is a wave of air that arises from complex mechanisms in the human body. It is assisted by three functional unit’s viz. generation of air pressure, regulation of vibration and control of resonators. Basically, speech is the ability to communicate thoughts and feelings by articulating sounds. The speech production mechanism is divided into two parts i.e. phonation and articulation. The phonatory organs consist of lungs and larynx. Phonation acts as a voice production system, as it creates the voice source sounds. This is done by adjusting the air pressure in the lungs and vocal cords vibration at the larynx. The two organs collectively adjust the loudness, prosody, pitch and quality of the voice of speech. The articulatory organs consist of the lips, tongue, lower jaw and the velum. They give modulations or resonances to the voice source and also produce additional sounds for some consonants. The properties of the acoustic resonator depend on the position of the articulatory organs. The larynx also takes a part in distinctions of voiced/voiceless articulation [18]. The phonatory and articulatory systems regulate each other mutually in sequential manner for producing voice. The vocal tract can be viewed as an acoustic filter on sounds originating at the larynx as it enhances some frequencies and attenuates others [19].

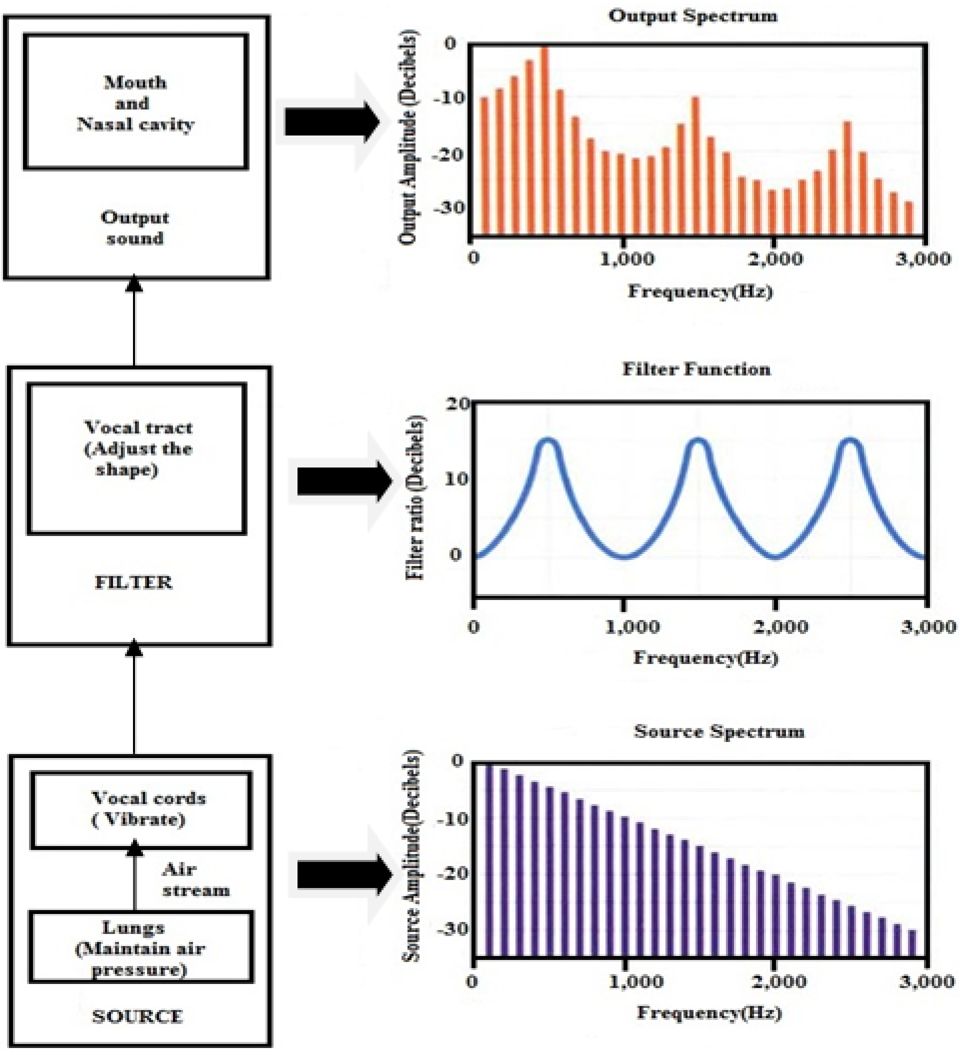

Figure 1: Descriptive Signal level analogy [19]

Voice is an indication of physical and mental state. Table 1 is the sleepiness hypothesis (i.e. educated guesses) relating physiological changes with the psychological state.

Table1: Fatigue induced physiological and psychological changes [2][20][21][22]

Effects on physical state	Effects on mental state
Respiration: 1. Reduced muscle stress causes: ● Decreased subglottal pressure ● Sluggish and periodic respiration Phonation: 1. Decreased muscle tension causes: ● Decrease in vocal fold tension, stiffness and viscosity ● Increase in vocal fold elasticity Articulation/ resonance: 1. Reduced muscle stress causes: ● Softening of vocal tract walls and hardening of pharynx 2. Reduced body temperature causes: ● Decreased heat conduction changes the laminar flow and turbulence Radiation: 1. Reduced muscle stress causes: ● Reduced lip spreading and facial expressions	Reduced cognitive ability: ● Adversely affects the speech planning and neuromuscular motor coordination processes

2. FACTORS AFFECTING ACQUISITION AND ANALYSIS OF SPEECH DATA FOR FATIGUE DETECTION

The factors that affect the acquisition and analysis of speech data are: (a) hardware selection, (b) recording software, (c) microphone preference, (d) impact of noise, (e) sampling rate, (f) number of speech samples, (g) file format, (h) hours awake and time of recording, (i) word spotting, and (j) overall system features viz. portability, cost efficiency, easy to use etc.[23]. The researcher needs to ensure that each stage and each component for acquisition and analysis of speech data are appropriate, so that they can adequately address their objective and optimize their result for accuracy and precision.

Various hardware configurations can be used to record the speech samples having low to high quality. The hardware selection for the most apt configuration depends on a number of features (e.g. Quality of recording, portability, ease of use etc.) which decide the level of fidelity. The different recording software provide different features (e.g. recording, analysing files and trimming) and different options viz. input mode (i.e. mono or stereo), mic sensitivity, sampling rate, file format, noise cut, low cut and output display for controlling the hardware setting. The microphone specifications and configurations are the most powerful features that determine the quality and reliability of the speech signal. The microphone offers different specifications viz. polar pattern (cardioids, omnidirectional), impedance (low, medium, high), sensitivity (low, medium, high), type (condenser, dynamic), frequency response (wide, narrow), connection (XLR, USB, 3.5mm), and positioning (i.e. distance, angle and type (viz. head mounted, table top and lapel)) [23] The signal can be altered due to external factors like environmental or additive noises. The advancement in technology improves the speech recognition ability even in noisy environments.

Analog to digital conversion involves sampling and quantization to convert a continuous physical quantity into digital number that represents the amplitude of physical quality at different instant of time. “The sampling rate is the number of the samples per second”. “The quantization level is the number of discrete levels of signal amplitude corresponding to the number of binary bits in each digital number”. The sampling rate and quantization level determine the quality of the speech signal recorded. The Nyquist theorem is the main principle which helps obtaining the optimal sampling rate. It states that “the number of samples needed to faithfully represent a signal is twice the highest frequency of interest present in the signal” (Nyquist, 2002). File format (i.e. the mode of data storage) also plays a very important part in the recording process. The Resource interchange file format (RIFF)(e.g.,.wav) and Audio interchange file format (AIFF)(e.g.,.aif) save data in uncompressed form using pulse code modulation (PCM) format. PCM format has a sampling rate of 44.1 kHz and 16 bit quantization. The quality and the fidelity of the recorded signal are ensured by this method [23].

Whitmore and Fisher (1996) and Roth et al. (1989) have observed a strong circadian trend, as the speech production system offer best performances during regular working hours, and worst during usual sleeping hours [24][25]. “Circadian means processes occurring periodically approximately in a 24-hour interval.” Sleep cycle follows the circadian trend and if sleep is interrupted it causes fatigue. That is why strong fatigue is noticed during usual sleeping hours. Therefore, the time of recording is quite vital in analysis of speech data for fatigue detection. All the phonemes in the human speech are not affected equally by fatigue. Sounds which need a greater average airflow are more sensitive to fatigue. Airflow is directly related driving pressure and resistance. The lungs generate the driving pressure and respiratory tract produces the resistance. The relationship of airflow to driving pressure and airway resistance can be represented as follows [26]:

$$F = P / R$$

In the above equation F represents airflow, P represents driving pressure, and R represents airway resistance.

Subject’s voice varies in synchrony with both level of fatigue and the time of sustained wakefulness [26].

Table2. Average airflow required to generate the speech sounds [26]

Average air flow required to generate the speech sounds	
Sound	**Average Airflow(mL/s)**
/t/	968
/p/	933
/d/	525
/g/	372
/l/	133
/m/	168
/z/	159

3. Literature review

Table 3 describes the summary of the work done by the researchers in detecting the level of fatigue by speech analysis. It also includes the number of participants, recording regime, stimuli and features for the detection of fatigue.

Table3. Literature Review

Author/ Year	Participants	Recording regime	Stimuli	Features	Remarks
Whitmore et al. (1996) [38]	12	1] 36 hours of sustained wakefulness. 2] Recordings were made after every 3 hours.	Two sentences: “Futility Magellan, this is (x y); The time is hr:min Zulu”. x : participant’s rank, y: name, and hr:min: time.	Fundamental Frequency (f0);Word duration	1] The results of the voice analysis were quite similar to results of the cognitive test and subjective tests of alertness. 2] Quality of speech follows the circadian trend, as it was at its best during normal working hours and the worst in usual sleeping hours. 3] Significant changes in f0 and word duration.
Bard et al. (1996) [27]	35	64 hours of sustained wakefulness.	Dialogue recorded during map task.	Speech length; Pause length	Speech duration and work performance measures indicated repercussions of medication and sleep deprivation.
Harrison et al. (1997) [28]	9	1] 36 hours of sustained wakefulness. 2] Recordings were made between 8-9 hours and 32-33 hours.	Reading a passage for approximately 3 minutes.	Intonation; Pitch	They found a loss of intonation (i.e. monotonic and flattened voices) between sleep and no sleep condition.

Greeley et al. (2006) [24]	2	1] 34 hours of sustained wakefulness. 2] Recordings were made 6 times in a span of 34 hours (10:00, 16:00, 22:00, 04:00, 10:00 and 16:00).	1] list of 37 words 2] list of 31 words	Formant frequencies; Mel-frequency cepstrum coefficients (MFCC)	1] Voice results obtained had great similarity with standardized experiments like Sleep Onset Latency (SOL) and Activity, Fatigue, Sleep, and Task Effectiveness. 2] The formant frequencies were related to participant's attentiveness, which was directly related to his/her fatigue level. 3] MFCC value changes with the participant's fatigue level.
Greeley et al. (2007)[26]	31	Participants are divided into 3 groups: Group 1: 1] 34 hours of sustained wakefulness. 2] Recordings were made after every 6 hours. Group 2: The testing period consisted of 3 nights, where the participants were allowed to sleep 2 hours each on their second and third nights. Group 3: Recordings were made after every 2 hours during a normal workday.	Group 1: subjects recited 31 unrelated words. Group 2: subjects recited eight fixed phrases. Group 3: subjects recited eight fixed phrases	Cepstral Coefficient	1] Subject's voice for speech sounds which need a greater average air flow varied in synchrony with both level of fatigue and the time of sustained wakefulness. 2] Sounds which need a greater average airflow were more sensitive to fatigue. 3] Speech analysis in this paper does not concentrate on a single, distinct parameter (such as pitch or duration) but, instead, analyzed the changes in a mathematical representation of the entire speech (i.e. the Cepstral components).
Krajewski et al. (2007)[29]	23	Sustained wakefulness during normal sleeping hours (8.00 p.m. to 4.00 a.m.).	German phrase, in form of a statement: "Ich suche die Friesenstraße" ["I´m searching for the Friesen Street"]".	Frequencies, bandwidths, and amplitudes of the F1-F5 formants; f0; Intensity; Jitter; Shimmer; Short-term fluctuations in energy; Mean; Standard deviation; Maximum; Minimum; Range, Positions and values of Maxima and minima; Harmonic-to-Noise ratio (HNR); Frequencies and amplitudes of the first 2 harmonics; MFCC.	They achieved 80.0% accuracy with simple linear classifier (LDA) and 79.4% with artificial neural network (ANN) classifier and after using an ensemble classification strategy (majority voting as meta-classifier) recognition rate of 88.2% was achieved.

Krajewski et al. (2008)[30]	21	1] Sustained wakefulness during normal sleeping hours (8.00 p.m. to 4.00 a.m.). 2] Recordings were made 4 times in a span of testing period (8.30 p.m., 9.00 p.m., 3.00 a.m., and 3.30 a.m.).	Sustained phonation of the "German vowel [a:]" for 2 second.	Intensity;f0; Linear predictive coding (LPC); Formants (Position and bandwidth); MFCC ; Linear frequency-cepstral coefficients (LFCC); Harmonics-to-noise ratio; Voiced segments duration; unvoiced segments duration.	1] A recognition ratio of eighty three percent was achieved in use of [:a] vowel by studying the different levels of performance between an active and fatigue state of a person. 2] Average harmonics-to-noise ratio increased for sleepy speaker.
Krajewski et al. (2008)[31]	12	Sustained wakefulness during normal sleeping hours (01.00 - 08.00 am).	Pilot-air traffic controller communication: "Cessna nine three four five lima, county tower, runway two four in use, enter traffic pattern, report left base, wind calm, altimeter three zero point zero eight".	Acoustic features (low-level descriptors, LLDs): f0; Intensity; Harmonics to-noise ratio; Formants; MFCC; LFCC; Duration of voiced–unvoiced segments; LPC; long term average spectrum(LTAS) Spectral Feature: Band-Energies; Roll-Off; Centroid; Long term average spectrum (LTAS)	1] SVM was proven to be the best model static acoustic feature vector. 2] It had a recognition rate of eighty six percent in predicting fatigue states (i.e. micro-sleep endangered sleepiness stages).
Krajewski et al. (2009)[17]	12	Sustained wakefulness during normal sleeping hours (01.00 - 08.00 am).	Pilot-air traffic controller communication: "Cessna nine three four five Lima, County tower, runway two four in use, enter traffic pattern, report left base, wind calm, Altimeter three zero point zero eight".	Perceptual and signal processing: f0, Formants, Cepstral Coefficients; Prosody: Pitch, Intensity, Rhythm, Pause Pattern, Speech Rate; Articulation; Speech Quality.	1] Acoustic features extracted from the stimuli contain information about sleepiness states. 2] SVM was the best model for the static acoustic feature vector and it had a recognition rate of eighty six percent in predicting fatigue states (i.e. micro-sleep endangered sleepiness stages).
Dhupati et al. (2010)[1]	12	36 hours of sustained wakefulness.	"*Now the time is* ______".	Voiced duration; Unvoiced duration; Response time; MFCC; EEG Based Parameters: Alpha and Theta band energy.	1] The duration of pauses between words seemed to increase. 2] Response time increased with increase in fatigue. 3] An increased trend was been observed in relative energy of alpha band indication of reduced alertness.

Vogel et al. (2010)[32]	18	1]24 hours of sustained wakefulness. 2] Recordings were made every 4 hours.	Automated and extemporaneous tasks, sustained vowel and a passage.	Timing : Total Speech Time, Mean Pause Length, Total Signal Time, Percentage Pause, Intensity and spectral tilt; Frequency: f0, Formants(F1-F4), Standard deviations (SD) and Coefficients of variances(CoV) of frequency (i.e. f0 SD, f0CoV, F4 SD, F4 CoV); Power (alpha ratio)	1] Clear changes in f0 variation (SD- standard deviation and CoV- covariance) were observed to be directly related to increasing fatigue level. 2] Formant patterns remained invariant despite increasing levels of fatigue, with the exception of F4 and F4 variation (SD/CoV). 3] The effect of fatigue on speech was found to be strongest just before dawn (after 22 hours). 4] Significant increases in total sample duration, total speech time and mean pause length were observed as levels of fatigue were amplified.
Zhang et al. (2010)[33]	Not disclosed	Recordings were taken at four different times (4:00 a.m., 10:00 a.m., 4:00 p.m., and 10:00 p.m.).	Six Chinese vowels	MFCC; LPCC	MFCC was found to be superior to LPCC.
Krajewski et al. (2010) [34]	17	Sustained wakefulness during normal sleeping hours (8.00 p.m. to 4.00 a.m.).	A long vowel [o:] extracted from a German phrase: “Rufen Sie den N[o:]tdienst” (“Please call the ambulance”).	NLD (Non-Linear dynamics) features: State space Features (i.e. sound pressure, Δ sound pressure, ΔΔ sound pressure), Fractal features (i.e. Cao’s minimum embedding dimensions), Entropy features (i.e. Lyapunov exponents); Speech emotion recognition (SER) feature set (e.g. f0, intensity, pause patterns, formants, cepstral coefficients, jitter).	1] When the level of fatigue increased in the subject, it influenced the speed production mechanism to generate nonlinear aerodynamic phenomena. 2] Nonlinear aerodynamic phenomena gives rise to turbulent air flow, NLD features provide additional information regarding the dynamics and structure of speech of fatigue person in comparison to the SER feature set.

Khokale et al. (2010) [35]	Not disclosed	Recordings were made at morning, afternoon, evening and night.	Not disclosed	f0; formant frequencies; cepstrum; short-time energy; Energy entropy; Power Spectral Density; Spectral Centroid.	1] Mental fatigue was observed in subjects that experienced a long duration of emotions like fear, aggression, while participants experiencing emotions like calm, cheerful were seen to have less fatigue levels. 2] It was seen that the first emotional group's standard deviation of short-time energy was greater. 3] The level of accuracy in detecting fatigue increased if the subject gave an emotional speech.
Krajewski et al. (2012) [36]	77	Sustained wakefulness during normal sleeping hours (8.00 p.m. to 4.00 a.m.).	Sustained phonation of the vowel /a:/ for three to five second.	Non-linear dynamics (NLD) features: State space features, Fractal features and entropy features; Phonetic features.	1] The combined feature sets of phonetic and NLD (Non-Linear dynamics) were observed to give some extra information that helped in improving the results. 2] Best performance for male and female speakers on the phonetic and the NLD feature set were achieved by bagging procedure.
Rashwan et al. (2013)[37]	8	Recording were made two times, one in the early morning and another in the late evening after a working day.	The participant is asked to make 2 phone calls.	MFCC; Statistical: Mean Variance, Median, Max, Min; Heart rate; Steering wheel, gas, Clutch, and brake pedals positions.	1] HMM (Hidden Markov Model) classifier was experimentally proven to be a good solution for car driver fatigue monitoring. 2] HMM performed better than Support Vector Machines

4. FEATURES EXTRACTION

Feature extraction is a procedure that extracts the useful information and discards the irrelevant and redundant information from the input data. It is necessary to extract those particular features from the speech signal that would reveal useful information regarding fatigue detection. It also improves the performance of classifiers. The features examined by different researchers to estimate the level of fatigue by speech analysis are described in the table 4.

Table 4: Features of the speech signal with reference

Feature	Reference
Fundamental frequency (f0)	[17][28][29][30][31][32][34][35][36][38]
Formant position (F1-F6)	[17][24][29][30][31][32][34][35][36]
Formant bandwidth (Fbw1–Fbw6)	[17] [29][30][31][32][34][35][36]
Duration of voiced–unvoiced segments	[1][17][27][30][31][32][34]
Mel frequency cepstrum coefficients (MFCCs)	[1][24][29][30][31][33][37]
Loudness(Intensity)	[17][29][31][34][32]
Cepstral coefficients	[17][26][34][35][36]
Harmonics-to-noise ratio (HNR)	[29][30][31]
Linear predictive cepstrum coefficients (LPCCs)	[30][31][33]
Zero crossing Rate	[1][27][30]
Shimmer	[17][29][34]
Jitter	[17][29][34]
Spectral Centroid	[31][35][36]
Linear predictive coding (LPC)	[30][31]
Non-linear dynamics (NLD) features	[34] [36]
Short-time energy	[29][35]
Speech duration	[32][38]
Mean	[29][37]
Variance	[32][37]
Standard Deviation	[29][32]
Long-term average spectrum (LTAS)	[31]
Power Spectral Density	[35]
Entropy	[35]
Maxima and minima	[29]
RMS Energy	[31]
Roll-off	[31]
Median	[37]
Speech Rate	[17]

The voice is an indication of physical and mental state and on this basis in literature many features are used to extract information from speech signal to analyse the fatigue state of an individual. But the fundamental frequency, loudness (intensity), formant frequencies, duration of voiced-unvoiced segments and MFCC are mostly analysed and concluded features.

Conclusion:

Fatigue is a critical element in many professions. Human voice has inevitable dependence on fatigue. The speech based fatigue measurement is of great importance and has many advantages over other measurement systems. This paper discussed the effects of long period of sustained wakefulness which induces fatigue and describes the effects of fatigue on the physiological and the psychological state of an individual which can be revealed by analysing speech. The results of the study done by researches in this field are significant to pilot, drivers, doctors, workers, employers, war fighters, public safety officials, air traffic control personnel and defence officers who are concerned with managing fatigue over long duration assignments. Hence there is a raising concern in developing a non-invasive measurement system that can be used to detect and manage fatigue in both health and workplace settings.

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