DEVELOPMENT AND EVALUATION OF THE FATIGUE AND DROWSINESS PREDICTOR

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Abstract

In 1998, by the discovery of the possibility of the human psychosomatic condition through the evaluation of a person's voice, the Electronic Navigation Research Institute started to develop the fatigue and drowsiness predictor for ATC controllers and aircraft pilots.

As a result of its development, the human voice analysis system based on the chaos theory, one field of modern mathematics, was developed in 2005. As a result of experiments, it was confirmed that the system could measure the degree of activity of the human cerebral neo cortex.

As a result of the ATC/CPDLC simulation carried out as part of a functional evaluation experiment of the human voice analysis system, it was predicted that the ATC workload would increase under the transition stage from current paradigm to the next CPDLC paradigm.

1 Introduction

Flight safety is heavily reliant on the performance of all those participating in aviation, and supporting the human element is a key to further enhancing aviation safety. If it were possible to monitor the conditions of ATC controllers and aircraft pilots in real-time, this would improve flight safety. In June 12, 2008, U.S. NTSB issued A-08-44 & 45 Safety Recommendation to the U.S. FAA to address a fatigue management system in aviation. In 2010, the Japanese Civil Aviation Bureau requested the Electronic Navigation Research Institute (ENRI) to develop a way for measuring and monitoring the ATC controllers' workload.

Crew fatigue is a very common problem, especially on long-haul flights crossing many time zones. If an increase in the probability of crew micro-sleep and/or human error could be detected, it might be possible to warn the pilot so that he or she should be relieved by other on-board crewmembers.

Historically, many methods have been proposed for measuring human fatigue, sleepiness and performance characteristics, but all these require that test subjects perform certain tasks specifically for the purpose of measuring them. All these methods therefore cannot measure the performance of a test subject doing a job task in real-time without imposing some sort of interference. However, for flight safety monitoring, a way of measuring crew performance in real-time that does not interfere with normal job activities is required.

In 1998, Hirose S. and Shiomi K. found that the time-averaged value of the first Lyapunov exponent calculated from a human voice signal changed according to the speaker's psychosomatic condition [1]. It seemed that the degree of fluctuation of the spoken voice increases when the speaker speaks hard. So the ENRI has been studying ways of measuring human performance by analyzing a person's voice since 1998.

If it were possible to derive the strange attractor of the human voice and to calculate its chaotic characteristics in real-time, this would enable human performance characteristics to be measured in real-time non-intrusively. The authors believe that the ENRI's human voice analysis system will provide a way to measure the ATC controllers' and the pilots' performance as the fatigue and drowsiness predictor.

2 Chaotic Human Voice Analysis

2.1 Strange Attractor of the Human Voice

Figure 1 shows the waveform of the "o" sound uttered by one of the authors. When the time series is sampled from the waveform as shown in Fig.1, the strange attractor of the human voice can be reconstructed in phase space as shown in Fig. 2 according to Takens' embedding theorem [2]. Moreover, when a strange attractor is reconstructed from a long single vowel sound, it can be analyzed approximately by methods proposed in current chaos theory [3]. It can be confirmed that the fractal dimension of the human voice is four or higher, and that the first Lyapunov exponent is positive.

Although the strange attractor in Fig. 2 is reconstructed in two-dimensional phase space, when calculating the first Lyapunov exponent of a time series it is usually reconstructed in a phase space of equal or higher dimension than the fractal dimension of the time series. In normal human voice chaotic analysis, the time series sampled from the voice signal should be embedded in four-dimensional phase space.

The authors thought that the strange attractor to which it seems that a certain orbit is fluctuating could be considered to be a visualization of man's homeostasis [4].

In 1998, the authors thought that the first Lyapunov exponent indicates the degree of tiredness of the speaker, since it seemed that the degree of fluctuation of the spoken voice increases when the speaker speaks hardly. However, it became clear that the thought mentioned above was not true based on the results of experiments carried out after 2000 [5].

At present in 2012, it is appropriate to us to think that the degree of fluctuation of speaker's voice is not directly indicates his or her tiredness. The authors understand that the degree of fluctuation shows the degree of activity of the Broca Field of the cerebral neo-cortex of the speaker.

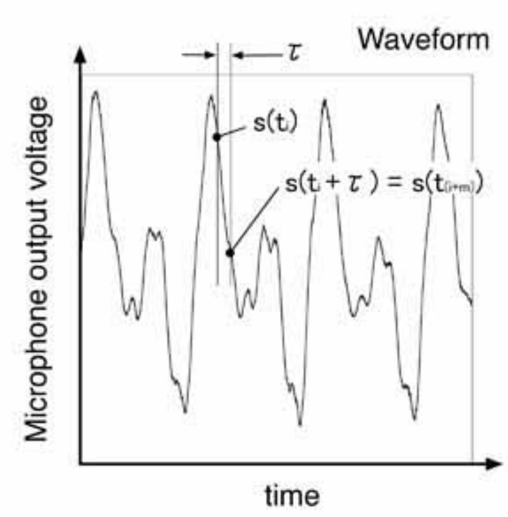

Fig. 1 "o" Sound Waveform

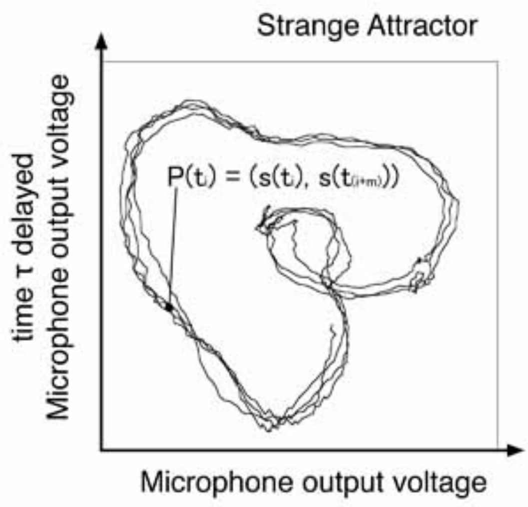

Fig. 2 "o" Sound Strange Attractor

2.2 Fluctuations of the Human Voice

A fatigue measurement experiment was carried out using a railroad-driving simulator at the Railway Technical Research Institute (Tokyo, Japan) for sixty days from Aug. 1 to Sep. 29, 2005 [5]. Eleven male university students and postgraduates of physical education at Tokyo Gakugei University, and one assistant professor, participated in the experiment. As a result of this experiment, it was confirmed that the degree of fluctuation of the spoken voice decreases after the speaker becomes fatigued.

Figures 3 and 4 each shows a strange attractor generated from a vocalized “o” sound obtained in the experiment mentioned above. Each strange attractor is generated from the last 80ms of the vocalized “o" sound of call-out made by railway drivers immediately before departure, “Shu-ppatsu Shinko!” (which means “Start and go ahead.”). The strange attractor shown in Fig. 3 was generated from a voice recording taken some tens of minutes after the start of a driving exercise in a railroad vehicle driving simulator, while Fig. 4 was generated from a voice recording taken after about five hours of simulated driving. Five hours of simulated railroad driving generally causes fatigue, and the authors hypothesized that the fluctuations in the uttered voice observed in Fig. 3 decreased in Fig. 4 due to this fatigue [5].

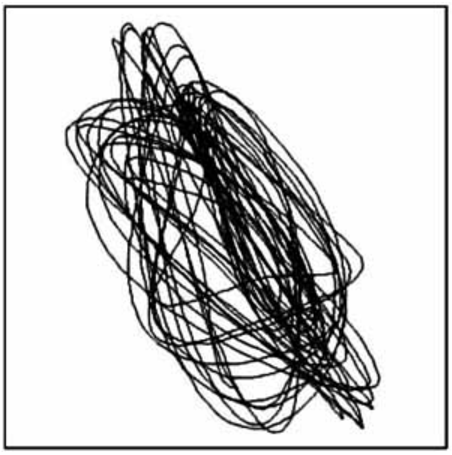

Fig. 3 Strange Attractor of vocalized “o” sound: the speaker is not fatigued.

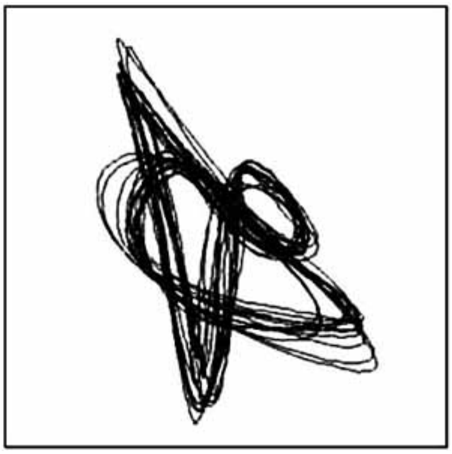

Fig. 4 Strange Attractor of vocalized “o” sound: the speaker is sleepy due to exhaustion.

2.3 Cerebral Exponent

Through many experiments mentioned above and others, Shiomi, one of the authors understood that the first Lyapunov exponent is not sufficient as a measure of the degree of fluctuation in the spoken voice. To calculate the first Lyapunov exponent, the system that generates the time series signal must be sufficiently stable, but since general speech contains many phonemes per second, it is not possible to calculate the first Lyapunov exponent directly from a complex general speech signal containing two or more vowels. The first Lyapunov exponent can be only calculated as a kind of estimation, when a single vowel was uttered for more than several seconds. Each different vowel gives a different first Lyapunov exponent. Since the first Lyapunov exponent is not appropriate enough to evaluate the fluctuation level of general speech, it is necessary to define a new index or exponent that could be called the time-local first Lyapunov exponent.

In 2002, the author succeeded in defining such indices of time-local chaotic characteristics, which are termed the “Cerebral Exponent micro (CEm)” and the “Cerebral Exponent Macro (CEM).” Since the degree of fluctuation of the uttered voice seemed to indicate the degree of activity of the speaker’s cerebrum, author Shiomi named the defined exponent “Cerebral Exponent micro/Macro.” The author also created an algorithm named SiCECA (Shiomi’s Cerebral Exponent Calculation Algorithm) to calculate the CEM rapidly [6].

As the result of fatigue measurement experiments, the CEM values calculated from the voice that reads a sentence show high correlation with the critical flicker frequency (CFF) measured at the same time. The CFF is a measurement that indicates the degree of arousal of the subjects, and was used under the notion that it held strong correlation to the degree of activity of the cerebral neo-cortex. The cross-correlation coefficient between the variation of CFF values and that of CEM is more than 0.6 under the data size of about 50 [5]. The CEM seems to show the state of the function of the neo-cortex, while the Hart Rate shows the state of the function of the autonomic nervous system [7].

From another experimental result, it was confirmed that the CEM (Reading-CEM) values calculated from the voice that reads a sentence, differ from the CEM (Callout-CEM) values calculated from utterances made without any reading a sentence. The author believes that this discrepancy may arise due to the fact that the reading-aloud voice for Reading-CEM is the subject's main task, but the call-out voice for Callout-CEM is a subtask.

Therefore, when the workload of the main task is relatively high, as a result of adjusting distribution of brain resources, although a degree of arousal is high, the phenomenon in which the Callout-CEM value decreases is observed. For example, the Callout-CEM value calculated from a voice when driving the track at the limited maximum speed of 120 km/h in the test course is often low as compared with the case of driving at 100 km/h [8]. Also, in the following ATC/CPDLC (Controller Pilot Data Link Communication) simulation experiments, the decrease of the CEM values by the rise of workload was observed.

In order to calculate CEM values that show high correlation with CFF values, it is necessary to set appropriate parameter values (embedding dimension, embedding delay time, evolution delay time, and so on) for SiCECA signal processing [9].

3 CPDLC Simulation

The authors carried out ATC simulation experiments for evaluating the ENRI's human voice analysis technique.

In the ATC simulation experiment, the workloads of ATC controllers under the conditions that the CPDLC would be introduced in the next ATC paradigm were evaluated.

It is expected that there will be some statistical differences between fluctuation levels of strange attractors reconstructed from ATC controllers' voices recorded under the simulation scenario of the current paradigm and that of the next paradigm, if the introduction of CPDLC changes the ATC workload, or not.

3.1 CPDLC Simulator

Figure 5 shows a general view of the ATC/ CPDLC simulator. The simulator consists of the ATC simulation server, and two client systems used as the user interface for participating in the ATC simulation. One of the two client systems is for a participant who participates I the ATC simulation as an ATC controller, and the other one is for a participant participating as an aircraft pilot.

Figure 6 shows the radar display image provided to the ATC controller. In the display image, the conventional aircraft are shown by triangles, and the aircraft (CPDLC-aircraft) that have the capability of data link communication are shown by circles. The call sign of the CPDLC-aircraft is also surrounded and expressed as a square frame in order to distinguish it from the call sign of the conventional aircraft.

Fig. 5 ATC/CPDLC Simulator

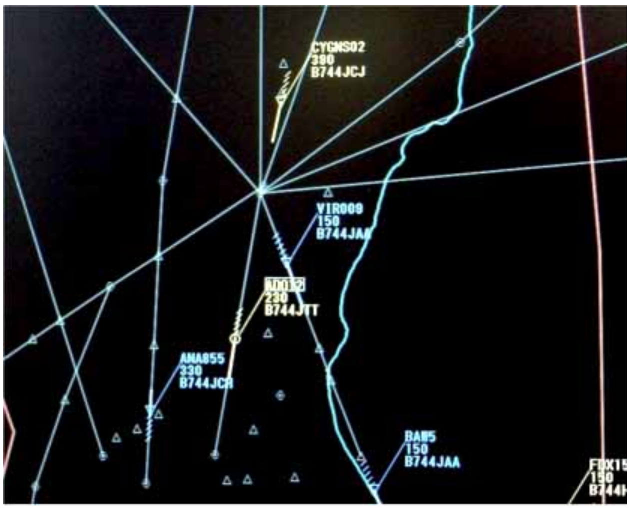

Fig. 6 Radar Display Image

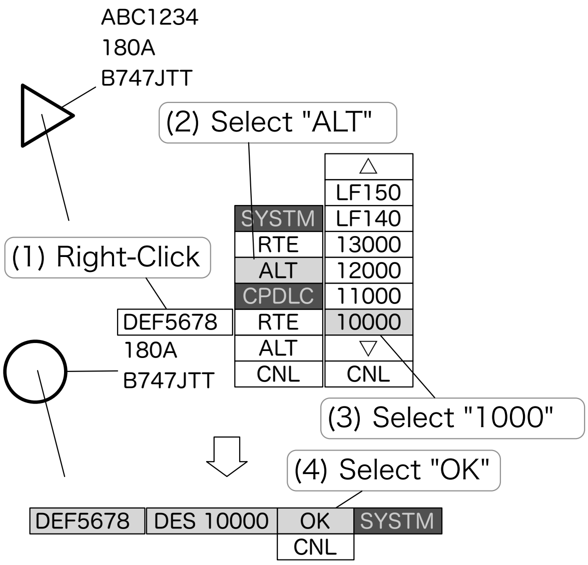

Fig. 7 CPDLC Instruction Sequence

Fig. 8 CPDLC Pop Up Menu

Fig. 9 ATC/CPDLC Simulation

Figure 7 shows the procedure for creating the message for CPDLC, "DEF5678 descend to flight altitude of 10,000." At first, the call sign of the target aircraft is right-clicked. Next, "ALT" is chosen from the pop-up menu. Next, "10000 (target flight level)" is chosen similarly. Finally, click "OK" after checking the CPDLC message. The pop-up menu for creating a CPDLC message is displayed on the radar image, as shown in Fig. 8.

For the ATC/CPDLC simulation, we prepared three kinds of simulation scenarios that can be processed in 30 to 40 minutes. Moreover, since the rate of the CPDLC-airplane was set at 0%, 30% and 80%, nine simulations per person were carried out.

Since the staff to play the role of a pilot had to also play the role of an ATC coordinator in performance of the ATC/CPDLC simulation, the pilot player had to sit beside the ATC controller as shown in Fig. 9.

3.2 Experiment Results

The experiment results of eight subjects are as follows. All test subjects were retired ATC controllers.

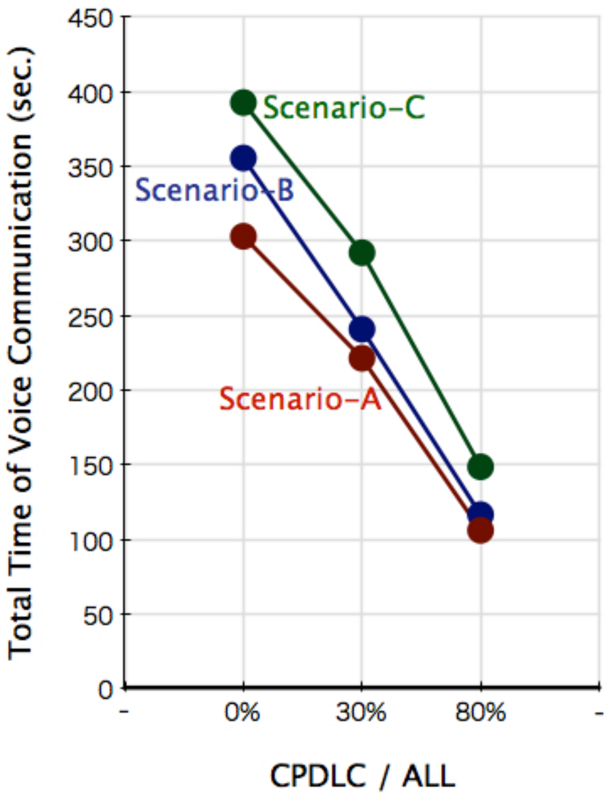

Fig. 10 Com. Time vs. Rate of CPDLC

As it is naturally expected that the rate of CPDLC-aircraft increases, the average of total time of voice communication decreases as shown in Fig. 10.

However, the ATC workload increases under the condition that the CPDLC-aircraft and conventional aircraft are intermingled as shown in Fig. 11. It is then confirmed that the ATC workload is not simply dependent on the length of communication time. Since there is no situation in which the ATC controller becomes sleepy in every simulation scenario, it is thought that the decrease of Callout-CEM values depends on the increase of thinking work.

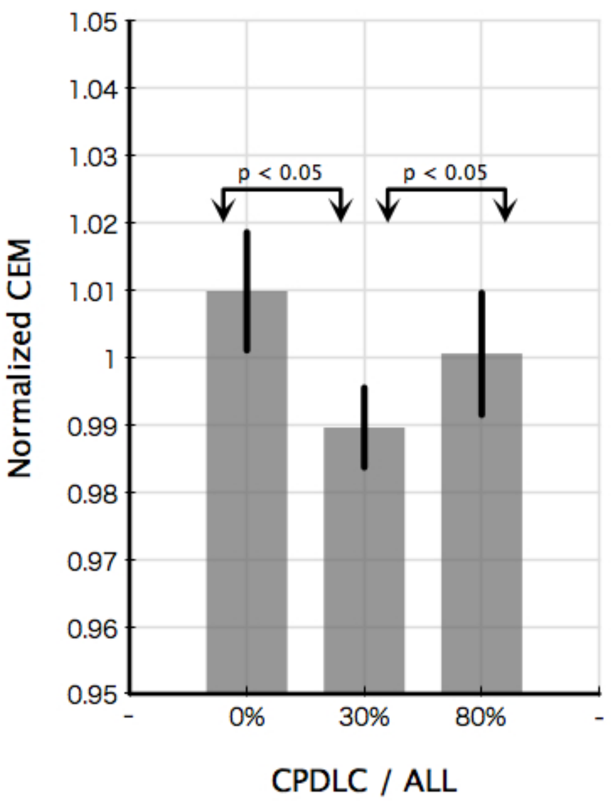

Fig. 11 CEM vs. Rate of CPDLC

The Student's t test was used for comparison between the "0% case" and "30% case" groups, and the "30% case" and "80% case" groups. A probability value $p < 0.05$ was considered statistically significant.

The above-mentioned experimental results are in agreement with the results of the interviews of the participants in the ATC/CPDLC simulation. Many ATC controllers said "Mistake in vocal communication with CDPLC-aircraft occurred frequently under the condition that the ratio of the CPDLC-aircraft is 30%."

4 Conclusion

ENRI developed the method to measure the degree of activity of the human cerebral neo-cortex. The measurement method is based on human voice analysis according to the chaos theory. By using this method, the workloads of ATC controllers, under the conditions that the CPDLC would be introduced in the next ATC paradigm, were evaluated. Increase in ATC workload is expected in the shift process to the CPDLC paradigm.

References

[1] Shiomi K and Hirose S. Fatigue and Drowsiness Predictor for Pilots and Air Traffic Controllers. *Proc. of 45th Annual ATCA Conference*, Oct. 2000.

[2] Takens F. Determining strange attractors in turbulence. *Lecture Note in Mathemat ics*, vol. 898, pp. 366–381, 1981.

[3] Sano M and Sawada Y. Measurement of the Lyapunov Spectrum from a Chaotic Series, *Physical Review Letters*, pp.1082-1085, 1985.

[4] Shiomi K. Voice Processing Technique for Human Cerebral Activity Measurement. *Proc. of IEEE-SMC 2008, P660,* Singapore, Oct. 2008.

[5] Shiomi K, Sato K and et.al. Experimental Results of Measuring Human Fatigue by Utilizing Uttered Voice Processing, *Proc. of IEEE-SMC 2008, P557,* Singapore, Oct. 2008.

[6] Shiomi K. Chaotic Voice Analysis and Model of Cerebral Dynamics, *Journal of Japan Society of Kansei Engineering,* Vol.4, No.1, pp.3-12, 2004.

[7] Shiomi K and Sato K. Chaotic Voice Analysis Method for Human Arousal Level Evaluation, *Proc. of ESREL 2010 Annual Conference,* Rhodes, Sep. 2010.

[8] Shiomi K, Sato K and et.al. Fatigue and Drowsiness Predictor, *Proc. of First International Symposium on Future Active Safety Technology toward zero-traffic-accident,* Tokyo, Sep. 2011.

[9] Shiomi K. Chaotic Voice Analysis Method for Human Performance Monitoring, *Proc. of ESREL 2009 Annual Conference,* Prague, Sep. 2009.

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