34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

# Preventing Lapse in Performance using a Drowsiness Monitoring and Management System

Kuan-Chih Huang, Tzyy-Ping Jung, *Senior Member*, Chun-Hsiang Chuang, Li-Wei Ko, Chin-Teng Lin, *Fellow IEEE*

***Abstract*—Research on public security, especially the safe manipulation and control of vehicles, has gained increasing attention in recent years. This study proposes a closed-loop drowsiness monitoring and management system that can estimate subjects' driving performance. The system observes electroencephalographic (EEG) dynamics and behavioral changes, delivers arousing feedback to individuals experiencing momentary cognitive lapses, and assesses the efficacy of the feedback. Results of this study showed that the arousing feedback immediately improved subject performance, which was accompanied by concurrent theta- and alpha-power suppression in the bilateral occipital areas. This study further demonstrated the feasibility of accurately assessing the efficacy of arousing feedback presented to drowsy participants by monitoring the changes in their EEG power spectra.**

## I. Introduction

Driver fatigue, drowsiness and inattention were considered the leading causes of car accidents [1-4]. Early detection of drivers' fatigue to sustain their cognitive capability and prevent accidents is highly desirable.

During the past few years, the public security has become an important issue, especially the safe manipulation and control of vehicles for preventing the growing number of traffic accident fatalities. Considering the issue of detecting driver's drowsiness, many studies measured physiological changes such as eye blinking, heart rate, or skin electric potential, and electroencephalogram (EEG), as a means of detecting human cognitive state [1-10]. For example, reports have shown that the human EEG could provide abundant information about the cognitive states such as alertness and arousal of individuals [1-2]. This study examines the feasibility of using the EEG to develop cognitive-state countermeasures for drowsiness detection and management.

*This work was supported in part by the UST-UCSD International Center of Excellence in Advanced Bio-engineering sponsored by the Taiwan National Science Council I-RiCE Program under Grant Number: NSC-100-2911-I-009-101, and in part by the Aiming for the Top University Plan of National Chiao Tung University, the Ministry of Education, Taiwan, under Contract 100W963. This work was also sponsored in part by US Office of Naval Research, Army Research Office (W911NF-09-1-0510) and Army Research Laboratory (W911NF-10-2-0022) , and DARPA.

Tzyy-Ping Jung is with the Institute of Engineering in Medicine and Institute for Neural Computation and Swartz Center for Computational Neuroscience, University of California, San Diego, 9500 Gilman Dr.#0559, La Jolla, CA 92093-0559, USA (corresponding author: phone: (858)822-7555; fax: (858)822-7556; e-mail: jung@sccn.ucsd.edu).

Kuan-Chih Huang, Chun-Hsiang Chuang and Chin-Teng Lin are with the Institute of Electrical Control Engineering and Brain Research Center, National Chiao-Tung University, 1001 University Rd., Hsinchu 300, Taiwan.

Li-Wei Ko is with the Department of Biological Science and Technology and Brain Research Center, National Chiao Tung University, 1001 University Rd., Hsinchu 300, Taiwan.

Several recent studies have proposed to develop quantitative techniques for continuous assessment of cognitive effort and workload by investigating the neurobiological mechanisms underlying EEG brain dynamics. Precisely, shifts in a subject's level of drowsiness, as indexed by changes in their task performance in sustained-attention experiments, were positively correlated with changes in occipital theta [10, 12] and alpha [12] power.

Research has also attempted to assist individuals in combating drowsiness and/or preventing lapses in concentration. Dingus et al. [13] and Spence et al. [14] proposed using warning signals to maintain drivers' attention. The warning signals could be auditory [14, 15], visual [16], tactile [17] or mixed [16]. Belz et al. [18] compared the efficacy of these warning signals and showed that drivers were less sensitive to visual alarms since they needed to pay attention to road conditions and the dashboard. Lin et al. [19] demonstrated that arousing tone-burst signals could help subjects to maintain their driving performance level. However, these studies mainly focused on the effects of arousing signals on behavioral performance. More recently, Jung et al. [21] explored EEG dynamics and behavioral changes in response to arousing auditory signals presented to individuals experiencing momentary cognitive lapses during a sustained-attention task. This study extends their study to propose a drowsiness monitoring and management (DMM) system that not only monitors the level of drowsiness and delivers arousing feedback to the drowsy drivers, but also assesses the efficacy of arousing feedback presented to the drowsy brain based on the EEG spectra.

## II. A Drowsiness Monitoring and Management System

This study proposes a closed-loop DMM system that comprises a driving performance monitoring system and a feedback-efficacy assessment system. Fig. 1 shows the flowchart of the drowsiness monitoring & management system. In our previous study [20], the driving performance monitoring system could continuously assess fluctuations in the alertness level of individuals by observing subjects' EEG changes. While the subjects were drowsy, the warning stimulus (1,750 Hz tone burst) could be delivered to them.

The feedback efficacy assessment system is designed to automatically recognize subjects' EEG changes following arousing feedback to assess the efficacy of the arousing feedback. To this end, feedback-induced EEG spectral features were selected and fed into machine-learning classifiers to detect ineffective warning feedback, and additional warning could be delivered to participants again.

978-1-4577-1787-1/12/$26.00 ©2012 IEEE 

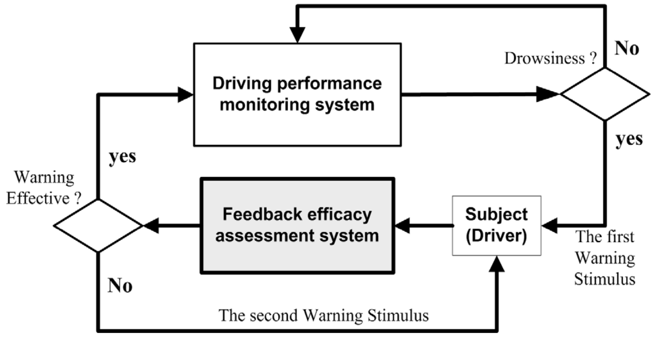



Figure 1. System flowchart of the proposed drowsiness monitoring & managemenet system

## III. Materials and Methods

### A. Subjects

Eleven subjects (aged from 18-29 years) participated in this lane-keeping driving experiment. All subjects had normal or corrected-to-normal vision and hearing. All experiments were started around 13:30 after lunch. Subjects were asked to practice to keep the car in the center of the cruising lane with the steering wheel at least for 5 min until their performance were satisfactory. Each subject had to perform the driving experiment for at least 60 min.

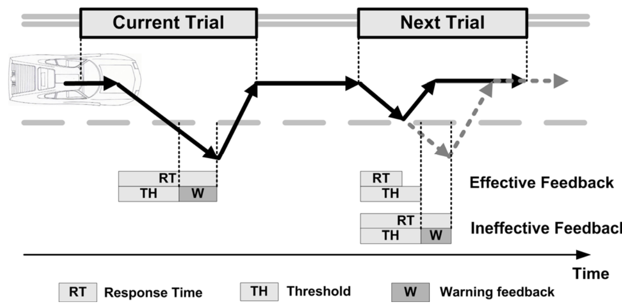
### B. Procedure

The VR scene emulated a car driving at a fixed speed of 100 km/hr on a highway. The car was randomly drifted away from the center of the cruising lane to mimic the consequences of a non-ideal road surface [19, 20]. This task required subjects to compensate the drifting by manipulating the steering to keep the car in the center of third cruising lane. The event-related task, a four-lane highway scene, is shown in Fig. 2(a). Fig. 2(b) illustrates the experimental paradigm and the temporal profile of a typical deviation event in the lane-keeping task. Each complete single trial started from the 3 sec before the car drifting to the subject's response offset. The response time (RT) was calculated from the deviation onset to the moment subject manipulated the steeling wheel. Each driving experiment lasted ~90 min, including a 5-min alert session and an 85-min experiment session. Lane-departure events were randomly introduced every 8-12 s, causing drift at a constant speed towards the curb or into the opposite lane with equal probability to continuously assess the driver's drowsiness level [22, 23].

During the first 5 minutes, subjects were asked to stay alert and the average RT of these alert trials was computed. We defined three times average RT as "Threshold" for drowsy trials. During the rest of the experiments, if subjects' RTs were over the set threshold, the system triggered a warning stimulus (e.g. auditory tone-burst) to the subject in half of these drowsy trials (marked as "current trial").

The lane-departure event immediately after the "current trial" was labeled as the "next trial". If the warning feedback was delivered to the subject, the trial condition was defined "with warning". The trials were labeled "without warning" if the warning sound was not delivered. In Fig. 2(b), for the next trials, some trials still had RTs longer than threshold, defined as "ineffective feedback"; others had RTs shorter than two times the mean alert RT, defined as "effective feedback".


(a)




(b)

Figure 2. (a) The four-lane highway scene used in the event-related lane-keeping task. (b) A bird's eye view of the event-related lane-departure event and the car moving trajectory in the current trial and next trial after effective and ineffective feedback.

### C. Data analysis

Our previous studies [6, 20] have shown that it is feasible to accurately detect drowsiness based on the spontaneous EEG spectra in several sustained-attention tasks. This study thus focuses on the concurrent EEG and subject behavioral changes following arousing auditory feedback to build a feedback efficacy assessment system. In the feedback efficacy assessment system, the effective or ineffective arousing feedback would be classified based on subjects' EEG spectra. Across subjects, a total of 171 trials received auditory feedback, including 30 ineffective trials and 135 effective trials. The trials with RTs between two to three times of the average alert RT, were not analyzed in this study.

The EEG signals were decomposed into temporally independent time courses presumably arising from distinct brain sources by independent component analysis (ICA) [24, 25]. Time courses of component activations were then transferred to frequency domain by fast Fourier transforms (FFT) with 1.5-s moving windows, advancing at an interval of 0.7s following subject response, resulting in 20 estimates of log EEG power between 4 and 12 Hz for each trial.

Components from each subject were categorized as brain activity or non-brain artifact (e.g., muscle, line noise or eye movement activity) by visual inspection of their scalp topographies, time courses and activation spectra. Across subjects, non-artifact components were then grouped into clusters according to their scalp maps, dipole source locations, and power spectra. The power spectral baselines of the same IC cluster were then averaged across subjects, and compared between conditions such as spectra of trials following effective versus ineffective feedback.

## IV. Results

### A. Behavioral improvements following auditory feedback

Fig. 3 shows the boxplots of RTs under different conditions for current (drowsy) and next trials. Current trials refer to lane-departure events in which the participants failed to respond with a compensatory wheel steering. In 50% of these non-responsive trials, the auditory tone of 1,750Hz was delivered to the participants (plotted in red). The next trials refer to trials following the current drowsy trials. The behavioral results showed that the arousing feedback was effective in recovering subjects' performance from the inattention or drowsy state. Over 80% of all trials with warning would have shorter RT (less than two times the average alert RT and even shorter than average alert RT) in the next trials. Statistical testing showed that the RTs of trials following warning were significantly shorter than those without warning ($p<0.01$). However, some of the next trials still had RTs comparable to the trials without feedback, indicating the arousing feedback was not effective in these trials. Fig. 3 (right panel), further separated trials following auditory feedback into effective (red) and ineffective (light blue) trials. The RTs of effective trials were significantly shorter ($p<0.001$) than those of the trials without warning and with ineffective warning. In fact, the RTs of ineffective trials were even longer than those of the trials without warning.

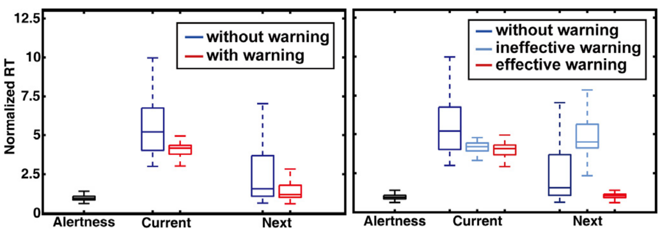



Figure 3. Left panel shows a comparison of RTs to lane-departure events between trials with (red) and without (blue) auditory feedback delivered after long-RT trials. Right panel shows the trials with effective (red) and ineffective light blue) feedback.

### B. EEG dynamics following auditory feedback

Fig. 4 shows the scalp map and the grand average of power spectral baselines of bilateral occipital components. The component cluster exhibited tonic broadband power increases below 25 Hz in trials subjects received feedback (blue and red traces), compared to alert trials (black traces). For the trials in which the feedback effectively rectified subjects' behavior (effective trials in Fig. 4 left panel), the spectral differences between current and next trials were statistically significant (brown horizontal line in Fig. 4 left panel) ($p<0.005$) and most prominent in the theta and alpha bands with over 5 dB to 10 dB decreases after receiving arousing feedback. In the ineffective trials (c.f. Fig. 4 right panel), the power spectra in current and next trials were almost the same. The next section tests the feasibility of detecting ineffective feedback based on the EEG spectra.

### C. A feedback efficacy assessment system

Fig. 5 shows the flowchart of feedback efficacy assessment system, which used principal component analysis (PCA), forward feature selection, backward feature selection, and orthogonal locality preserving projection (OLPP) to select features from spectra of the bilateral components. This study then employed support vector machine (SVM) [26], Gaussian maximum likelihood classifier (ML) [27] and k-nearest neighbor classifier (KNN) [28] to estimate, based on extracted component features, if next trials would have RTs shorter than two times or longer than three times the average RT. If the system detected the warning feedback was not effective, the warning could be delivered to the users again.

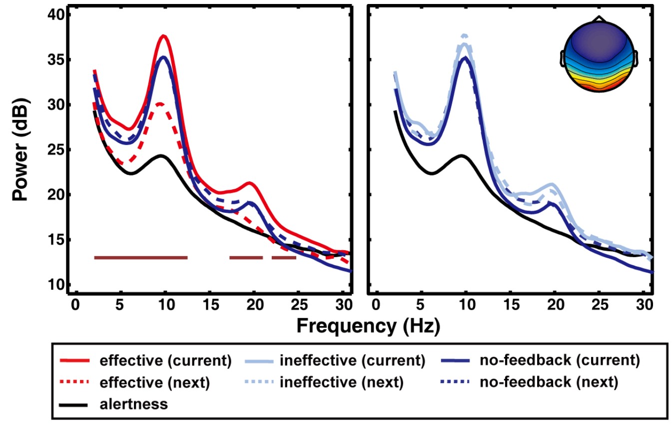



Figure 4. The mean baseline spectra of effective and ineffective trials before (current) and after auditory (labeled next) feedback, compared to those of alert and no-feedback trials.

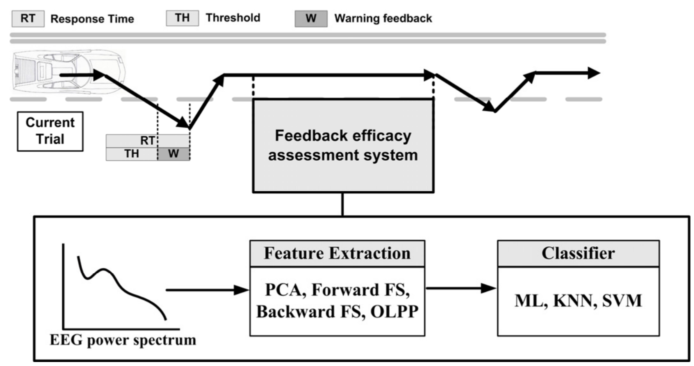



Figure 5. The elements of feedback efficacy assessment system and its processing flowchart.

Fig. 6 shows the classification results of the trials with effective and ineffective feedback. The accuracies of ML, KNN and SVM classifiers were all above 70%, except ML applied to the spectra data without using any feature extraction. Some of the accuracies, e.g. PCA plus ML, were even exceeded 75%. The differences in accuracies were not statistically significant across different feature extraction methods. The results also showed that, without feature extraction, the SVM classifier could still reach classification accuracy above 75 %.

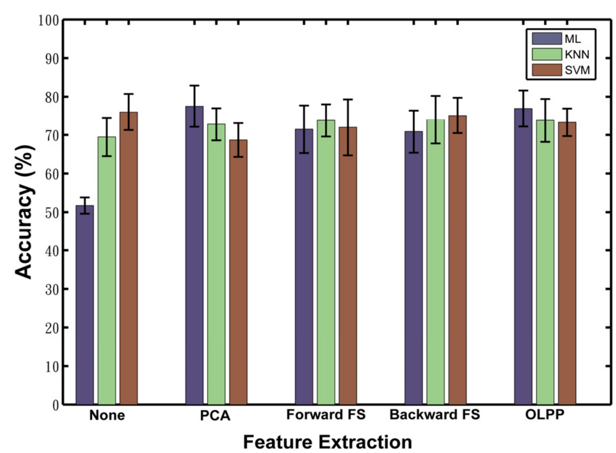



Figure 6. The classification results of using different feature extractions and classifier.

## V. DISCUSSIONS AND CONCLUSIONS

This study quantitatively showed that the auditory feedback aroused the subjects and triggered prompt compensatory responses such that the RTs of next lane-departure trials were significantly shorter than those of trials without auditory feedback (cf. Fig. 3). A significant improvement in subjects' behavioral performance was obtained in both current and next trials. Note that the RTs of trials following insufficient feedback were longer than those of trials without feedback. It could be attributed to the fact that in those trials, the subjects were severely drowsy and failed to fully recover from sleepiness even with the help of the feedback. Because the subjects were extremely drowsy, their RTs for the next lane-departure events tend to be longer than the averaged RTs of trials without feedback.

This study also showed that the occipital components exhibited significant theta- and alpha-power suppression following auditory feedback. These results suggested that arousing feedback assisted subjects in reducing their drowsiness level, reflected in both behavioral performance and brain activities. Furthermore, the theta- and alpha-band power of the trials following effective feedback was significantly lower than that of the trials following ineffective trials (cf. Fig. 3).

The proposed feedback efficacy assessment system could assess the efficacy of arousing feedback presented to the drowsy subjects based on the changes in the EEG power spectra from the moments immediately after the feedback. This demonstration might lead to a practical closed-loop DMM system that combines a drowsiness monitoring system [6, 20] and a feedback efficacy assessment system.

The current study used behavioral responses to trigger auditory feedback because, as the first study in assessing the efficacy of feedback, it is important to know exact occurrences of behavioral lapses. Our future work will replace the detection of behavioral lapses with the EEG-based alertness monitoring system previously reported in [6, 20].

## REFERENCES


[1] S. Makeig and M. Inlow, "Lapses in Alertness - Coherence of Fluctuations in Performance and Eeg Spectrum," *Electroencephalography and Clinical Neurophysiology,* vol. 86, pp. 23-35, Jan 1993.

[2] S. Makeig and T. P. Jung, "Changes in alertness are a principal component of variance in the EEG spectrum," *Neuroreport,* vol. 7, pp. 213-6, Dec 29 1995.

[3] P. Philip, J. Taillard, M. A. Quera-Salva, B. Bioulac, and T. Akerstedt, "Simple reaction time, duration of driving and sleep deprivation in young versus old automobile drivers," Journal of Sleep research, vol. 8, pp. 9-14, 1999.

[4] A. Campagne, T. Pebayle, and A. Muzet, "Correlation between driving errors and vigilance level: influence of the driver's age," Physiology & behavior, vol. 80, pp. 515-524, 2004.

[5] S. Makeig and T. P. Jung, "Tonic, phasic, and transient EEG correlates of auditory awareness in drowsiness," *Brain Res Cogn Brain Res,* vol. 4, pp. 15-25, Jul 1996.

[6] T. P. Jung, S. Makeig, M. Stensmo, and T. J. Sejnowski, "Estimating alertness from the EEG power spectrum," *IEEE Trans Biomed Eng,* vol. 44, pp. 60-9, Jan 1997.

[7] S. Makeig, T. P. Jung, and T. J. Sejnowski, "Awareness during drowsiness: dynamics and electrophysiological correlates," *Canadian Journal of Experimental Psychology-Revue Canadienne De Psychologie Experimentale,* vol. 54, pp. 266-73, Dec 2000.

[8] R. S. Huang, T. P. Jung, A. Delorme, and S. Makeig, "Tonic and phasic electroencephalographic dynamics during continuous compensatory tracking," *Neuroimage,* vol. 39, pp. 1896-909, Feb 15 2008.

[9] M. A. Schier, "Changes in EEG alpha power during simulated driving: a demonstration," *International Journal of Psychophysiology,* vol. 37, pp. 155-62, Aug 2000.

[10] S. K. Lal and A. Craig, "Driver fatigue: electroencephalography and psychological assessment," *Psychophysiology,* vol. 39, pp. 313-21, May 2002.

[11] M. R. Peiris, R. D. Jones, P. R. Davidson, and P. J. Bones, "Detecting behavioral microsleeps from EEG power spectra," *Conf Proc IEEE Eng Med Biol Soc,* vol. 1, pp. 5723-6, 2006.

[12] J. A. Horne and S. D. Baulk, "Awareness of sleepiness when driving," *Psychophysiology,* vol. 41, pp. 161-165, Jan 2004.

[13] T. A. Dingus, D. V. McGehee, N. Manakkal, S. K. Jahns, C. Carney, and J. M. Hankey, "Human factors field evaluation of automotive headway maintenance/collision warning devices," *Human Factors,* vol. 39, pp. 216-29, Jun 1997.

[14] C. Spence and J. Driver, "Inhibition of return following an auditory cue. The role of central reorienting events," *Exp Brain Res,* vol. 118, pp. 352-60, Feb 1998.

[15] C. T. Lin, T. T. Chiu, T. Y. Huang, C. F. Chao, W. C. Liang, S. H. Hsu, and L. W. Ko, "Assessing effectiveness of various auditory warning signals in maintaining drivers' attention in virtual reality-based driving environments," *Percept Mot Skills,* vol. 108, pp. 825-35, Jun 2009.

[16] Y. C. Liu, "Comparative study of the effects of auditory, visual and multimodality displays on drivers' performance in advanced traveller information systems," *Ergonomics,* vol. 44, pp. 425-42, Mar 15 2001.

[17] C. Ho, H. Z. Tang, and C. Spence, "Using spatial vibrotactile cues to direct visual attention in driving scenes," *Transportation Research Part F-Traffic Psychology and Behaviour,* vol. 8, pp. 397-412, Nov 2005.

[18] S. M. Belz, G. S. Robinson, and J. G. Casali, "A new class of auditory warning signals for complex systems: Auditory icons," *Human Factors,* vol. 41, pp. 608-618, Dec 1999.

[19] C. T. Lin, K. C. Huang, C. F. Chao, J. A. Chen, T. W. Chiu, L. W. Ko, and T. P. Jung, "Tonic and phasic EEG and behavioral changes induced by arousing feedback," *Neuroimage,* vol. 52, pp. 633-642, Aug 15 2010.

[20] C. T. Lin, R. C. Wu, T. P. Jung, S. F. Liang, and T. Y. Huang, "Estimating driving performance based on EEG spectrum analysis," *Eurasip Journal on Applied Signal Processing,* vol. 2005, pp. 3165-3174, 2005.

[21] T. P. Jung, K. C. Huang, C. H. Chuang, J. A. Chen, L. W. Ko, T. W. Chiu and C. T. Lin, "Arousing Feedback Rectifies Lapse in Performance and Corresponding EEG Power Spectrum," *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE*, pp. 1792 – 1795, 2010.

[22] R. S. Huang, T. P. Jung, and S. Makeig, "Multi-scale EEG brain dynamics during sustained attention tasks, " *Proc. of the IEEE ICASSP*, vol. 4, 1173-6, 2007.

[23] R. S. Huang, T. P. Jung, and S. Makeig, "Event-related brain dynamics in continuous sustained-attention tasks." *In D.D. Schmorrow, L.M. Reeves (Eds.): Augmented Cognition, HCII 2007*, LNAI 4565, 65–74, 2007.

[24] A. J. Bell and T. J. Sejnowski, "An information-maximization approach to blind separation and blind deconvolution," *Neural Comput,* vol. 7, pp. 1129-59, Nov 1995.

[25] S. Makeig, T. P. Jung, A. J. Bell, D. Ghahremani, and T. J. Sejnowski, "Blind separation of auditory event-related brain responses into independent components," *Proc Natl Acad Sci U S A,* vol. 94, pp. 10979-84, Sep 1997.

[26] C. C. Chang and C. J. Lin. LIBSVM: A Library for Support Vector Machines. Online available: http://www.csie.ntu.edu.tw/~cjlin/libsvm, 2001.

[27] J. P. Hoffbeck and D. A. Landgrebe, "Covariance matrix estimation and classification with limited training data," IEEE Trans. Pattern Anal. Mach. Intell., vol. 18, no. 7, pp. 763-767, July 1996.

[28] S. D. Bay, "Nearest neighbor classification from multiple feature subsets," Intelligent Data Analysis, vol.3, no.3, pp.191-209, 1999.