Application of Heart Rate Variability Analysis to Electrocardiogram Recorded Outside the Driver’s Awareness From an Automobile Steering Wheel

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Background Approximately 5% of motor vehicle deaths are assumed to be occur because of a cardiac event thought to be triggered by multiple factors. One important factor is an imbalance of sympathetic and parasympathetic nervous activities, which can be measured by analyzing heart rate variability (HRV). Therefore, a system has been developed to make electrocardiographic (ECG) recordings outside the driver’s awareness from the steering wheel (steering-ECG) with an algorithm to remove noise.

Methods and Results Steering-ECG and ECG from a chest lead (chest-ECG) were recorded simultaneously in 10 normal subjects while they were driving for 90 min. For each of 4 parameters (instantaneous heart rate, low- and high-frequency components of HRV, and the ratio of these components in all subjects), mutual information was used to examine whether the fluctuation from the steering-ECG resembled that from the chest-ECG. The mutual information of each parameter was larger than 0.047 with 95% confidence interval (mutual information values vary from 0 to 1; threshold of significance: 0.047). Hence, the fluctuation of each steering-ECG parameter resembled its chest-ECG counterpart.

Conclusions This system heralds a new driver-safety strategy by reporting alteration of autonomic nervous activity during driving. (Circ J 2008; 72: 1867–1873)

Key Words: Autonomic nervous system; Heart rate variability; Sudden cardiac death; Traffic accidents

The annual number of sudden cardiac deaths (SCD) is increasing in Japan, and is estimated by the Japan Heart Foundation to be more than 50,000. In the United States, SCD is the greatest cause of natural death, causing more than 400,000 adult fatalities each year and it is the most common lethal manifestation of heart disease. Its high incidence makes SCD a major challenge in public health. In most cases, the mechanism is abrupt occurrence of ventricular tachyarrhythmia, rapidly progressing to ventricular fibrillation, causing cardiac pump failure with unconsciousness. It is supposed that SCD sometimes occurs while the subject is driving an automobile. There also may be cases in which a patient receives a warning of imminent SCD, and is able to survive, or at least prevent injury to others. For example, a Japanese newspaper (March 31, 2004) reported, “While a bus driver (47 years old) was driving a bus, he called his office and complained of chest discomfort. He was taken to a hospital and died of acute myocardial infarction 2 h later”. Although such cases can easily be found on web sites, there has been little reported study. Lam and Lam reported that among older drivers aged 60 or more in New South Wales, Australia, from 1996 to 2000, 409 (1.1%) of 36,595 were recognized as having suffered a sudden illness immediately prior to a crash, and that 254 (0.7%) of those episodes resulted in the driver’s death and injury. According to a review from the Accident Research Centre of Monash University, Melbourne, Australia, the percentage of natural driver deaths out of all vehicle deaths was reported to vary from 0.2% to 19% in 10 studies. That review listed 19 studies in total in its Appendix; it was reported that the percentage of cardiovascular disease in drivers who met natural deaths was from 68% to 97%. We speculated, on examination of a summary of those studies, that the total number of natural driver deaths and the number of natural driver deaths because of cardiac events were, respectively, 5–10% and approximately 5% of all vehicle deaths.

Although there have been some trials of monitoring the electrocardiographic (ECG) of drivers, no automobile equipped with such a system has ever been marketed, because the ECG recording was largely contaminated by noise. Therefore, we developed new electrodes for installation on a steering wheel, through which an ECG limb lead can be recorded with suppression of noise. However, some artifacts are still present as a result of the physical movements accompanying handling of the steering wheel and as a result of jolts because of road conditions. Such artifacts are inevitable, because a driver does not remain still while seated, as would be the case during the recording of a standard ECG. At the present time we have not yet succeeded in recording the entire PQRS pattern of waves in the ECG from a steering wheel (steering-ECG), because of contamination of the baseline by noise. Therefore, the first of our
The goals in the present study were: (1) confirmation of the correctness of the steering-ECG, (2) confirmation of the correctness of the RR intervals of the steering-ECG, and (3) confirmation of the correctness of the heart rate variability (HRV) analysis of the steering-ECG, when a driver remains still while gripping the steering wheel by both hands. However, noise unavoidably contaminates the steering-ECG, because the driver is not lying calmly on a bed but is handling a steering wheel. Although an ECG from a chest lead (chest-ECG) was recorded simultaneously as a reference in order to examine the correctness of the steering-ECG, the chest-ECG was also unavoidably contaminated. Hence, it was impossible to continuously find 1-to-1 correspondence between the R waves of a steering-ECG and those of a chest-ECG. However, it was possible to observe the fluctuations of HRV by ignoring those inevitable artifacts. Our other goal was to evaluate the fluctuation of autonomic nervous activity from the HRV analysis of the steering-ECG despite the noise. We examined whether fluctuations of sympathetic and parasympathetic nervous activities measured from a steering-ECG were consistent with those from a chest-ECG.

**Methods**

**Subjects**

We simultaneously recorded the ECG from a chest lead and from a steering wheel for each of 10 normal subjects driving an automobile for 90 min. Next, the subjects remained seated in the driver’s seat gripping the steering wheel with both hands during 1 min of recording.

**Steering Wheel**

We refurbished the steering wheel of an automobile by installing a pair of electrodes around the grip site on each side (Fig 1). One electrode of the right pair was a (–) electrode, and the other, an indifferent electrode. One electrode of the left pair was a (+) electrode, and the other, an indifferent electrode. From these electrodes we made ECG recordings that corresponded to the standard ECG lead I. The electric wires from the installed electrodes were connected to a signal amplifier set up in the front of the automobile through a spiral cable within the steering wheel. We carefully kept the horn and air bag intact for safety purposes. The recorded signals were 1–5 mV, and were amplified 1,700-fold. A bandpass filter of 0.2–35 Hz was used to remove noise. With an AD converter, the signals from the steering wheel lead were sampled at 200 Hz. We consecutively searched the R waves of the steering-ECG and chest-ECG visually on screen. We examined whether the R waves of the steering-ECG corresponded in a regular 1-to-1 fashion with the R waves of the chest-ECG. The R waves that did correspond to each other in this way were represented as {steering-Rk} and {chest-Rk}. Intervals of {steering-RRk} and {chest-RRk} were compared to identify errors because of the filtering of the steering-ECG.

**Calculation of correlation coefficient (r) between the candidate and templates**

\[ r \geq 0.7? \]

Yes

The candidate is temporarily classified as a new template.

No

The candidate is classified as QR W wave. The QR W wave of the maximum r replaces a template which matches QR W waves the least frequently.

**Searchi ng candidates for QR W wave by a peak-detection algorithm from first differentiation of digitized ECG**

Slicing off a range including each candidate

Have there been any templates of QR W wave already?

Yes

Calculation of correlation coefficient (r) between the candidate and templates

No

The candidate is temporarily classified as a new template.

**Fig 2. Flow chart for detecting QR W waves. ECG, electrocardiographic.**

There were 3 chest electrodes served by a (+) electrode on V5 of the left chest, a (–) electrode below the right clavicle, and an indifferent electrode below the left clavicle. This corresponded to lead II of a standard ECG. These electrodes were connected to an electrocardiograph (DPA-250S; Dia Medical System Co, Tokyo; time constant=1.5 s, low-pass filter of 0.7–30 Hz). The signals were transferred to an AD converter and were sampled at 200 Hz.
Automated Detection of QRS Waves and Measurement of RR Intervals

The QRS waves were detected according to a flow chart, which we newly propose (Fig 2). In a preliminary study, we examined the reliability of the algorithm by applying it to the electrocardiograms of the PhysioBank, which are freely available and downloadable digitized data (sampling rate 250 Hz). Our algorithm could detect not only normal QRS waves, but also abnormal QRS waves, as shown in Fig 3. After detecting QRS waves, the RR intervals, \{I_n\}, were measured as the intervals of the peaks of 2 successive QRS waves. As the subject sitting in the driver's seat did not remain still, outliers of RR intervals were always observed. Outliers were excluded as follows: (1) calculation of the MI and SDI (the mean value and standard deviation of \{In\}); (2) exclusion of outliers as \(I_n > M_I + 2SDI\) or \(< M_I - 2SDI\), and representation of those intervals remaining after exclusion of the outliers as \(\{J_n\}\); (3) calculation of the standard deviation of \(\{J_n\}\) (expressed as the SDJ); (4) calculation of the median, \(Med_{J_n}\), of a set consisting of 11 consecutive intervals, \(\{J_{n-5}, J_{n-4}, \ldots, J_n, J_{n+3}, \ldots, J_{n+5}\}\) for each interval (indexed as \(J_n\)); (5) consecutive search of outliers as \(J_n > Med_{J_n} + SDJ\) or \(< Med_{J_n} - SDJ\); and (6) replacement of each of the outliers by \(Med_{J_n}\) so that the intervals after the replacement could be regarded as RR intervals, \(\{RR_n\}\).

Frequency Analysis

A smoothed instantaneous heart rate time-series was constructed from the RR-intervals and sampled at 8 Hz, according to Berger's method. The data length of an epoch was 64 s. The confidence in spectral estimates could be enhanced by dividing the data into 5 epochs and by ensemble averaging of Welch's method. To reduce the loss of stability, the data were divided using a 50% overlap. Linear trends were removed from the data, and the data were tapered by use of a Hanning window. Next, a fast Fourier algorithm was used. We calculated the low-frequency component (LF: 0.04–0.15 Hz) as a parameter of combined sympathetic and parasympathetic activity, the high-frequency component (HF: 0.15–0.40 Hz) as that of parasympathetic activity, the ratio LF/HF as that of sympathetic activity, for each epoch. The natural logarithms of LF, HF, LF/HF, namely, \(ln(LF)\), \(ln(HF)\), and \(ln(LF/HF)\), were used to make these distributions approximate to normal distribution. The entire length of 1 record of ECG was 90 min, the data length of 1 epoch was 64 s, and 2 consecutive epochs were overlapped by 50%. Hence, the total number of epochs was at most 168 (∼90 min/32 s).

Because the subject sitting in the driver's seat did not remain still and sometimes gripped the steering-wheel with only a single hand, more artifacts appeared in the steering-ECG than in the chest-ECG, such that normal QRS waves were not recorded frequently. Hence, we took 2 steps to examine the reliability of HRV analysis of the steering-ECG.

First, we compared \(ln(LF)\), \(ln(HF)\), and \(ln(LF/HF)\) of \(\{steering-RRk\}\) with those parameters of \(\{chest-RRk\}\), because \(\{steering-RRk\}\) corresponded in a regular 1-to-1 fashion with \(\{chest-Rk\}\). Each pair of \(R_k\) of \(\{chest-Rk\}\) and \(\{steering-Rk\}\) was consecutively searched visually on screen. We were able to examine the reliability of the hardware system by the first step. The correlation coefficients between the chest-ECG and steering-ECG for each parameter were calculated. The correlation coefficients were considered significant at \(p<0.05\).

Second, it was necessary to examine the reliability of the automated detection of QRS waves and measurement of RR intervals for the practical use of our system. According to the algorithm, the outliers in \(\{I_n\}\) of the steering-ECG were more frequently replaced by \(Med_{J_n}\) than those in \(\{I_n\}\) of the chest-ECG. We examined whether \(ln(LF)\), \(ln(HF)\), and \(ln(LF/HF)\) of the steering-ECG were reliable, despite such a disadvantage. We calculated the moving average of the subsequent 5 epochs for \(ln(LF)\), \(ln(HF)\), and \(ln(LF/HF)\), and instantaneous heart rate (HR): \(m-ln(LF)\), \(m-ln(HF)\), \(m-ln(LF/HF)\), and \(m-HR\). We constructed a time series of 4 parameters for the chest-ECG and steering-ECG.

Mutual Information

We drew graphs of the fluctuations of \(m-ln(LF)\), \(m-ln(HF)\), \(m-ln(LF/HF)\), and \(m-HR\) for the chest-ECG and steering-ECG. In order to compare the fluctuation of each parameter of the steering-ECG with that of the chest-ECG, we calculated the mutual information between them. This mutual information method was used to gauge the likeness between them. We calculated the mutual information values, according to an algorithm proposed by Fraser and Swinney and used in our previous study. For a couple of time series, \(\{x(t)\}\) and \(\{y(t)\}\), we measured how dependent the values of \(y(t)\) were on the values of \(x(t)\). We made the assignment \([s,q]=[x(t),y(t)]\) to consider a general coupled system \((S,Q)\). For example, \(\{x(t)\}\) was the time series of the moving averages of \(m-ln(LF)\) for chest-ECG and \(\{y(t)\}\) was the time series of moving averages of \(m-ln(LF)\) for the steering-ECG. Mutual information is defined as the answer to the question, “Given a measurement of \(s\), how many bits on average can be predicted about \(q\)?:”
\[ I(S,Q) = \int P(s,q) \log \frac{P(s,q)}{P(s)P(q)} \, ds \, dq, \]

where (1) \( S \) and \( Q \) denote the systems, (2) \( P(s) \) and \( P(q) \) are the probability densities at \( s \) and \( q \), respectively, and (3) \( P(s,q) \) is the joint probability density at \( s \) and \( q \). The data length is \( 2^n \). The algorithm is as follows: (1) an \( x-y \) plot is normalized into a square: each value \( W_i (=x(t) \text{ or } y(t)) \) was replaced by an integer \( N_i; 1 \leq N_i \leq 2n; \) if \( W_i < W_j, N_i < N_j; \) if \( W_i = W_j \) and \( i < j, N_i < N_j \), so that each of the values of \{x(t)\} and \{y(t)\} is 1-to-1 replaced by an integer from 1 to \( 2^n \); (2) it is successively divided into smaller squares; (3) a value for the dependence of \( y(t) \) on \( x(t) \) is calculated in each square; and (4) mutual information is the average of those values weighted by respective areas. Even if there is not significant correlation in the entire square, any significant correlation in the smaller squares is taken into the final correlation by weighting by the respective areas. Therefore, mutual information is considered to be applicable more generally than correlation coefficient of regression analysis. The larger the value of mutual information is for \( (S,Q) \), the stronger is the mutual dependence between \( S \) and \( Q \). The data length was \( 2^7 (=128) \). If \( S=Q \), the correlation between them should be perfect. Then, \( I(S,Q)=n \), where the data length is \( 2^n \), because the algorithm is developed to the discrete case. The mutual information value between the same 2 time series is \( n \). Hence, mutual information values were normalized by \( n \); that is, these values were divided by \( n \), resulting in values between 0 and 1. If the mutual information value was larger than or equal to 0.047, the correlation was taken to be strongly correlated, on the basis of our previous report.

**Results**

**Hardware System**

Although small HF noise still contaminated the baseline, the reproduced signals demonstrated the characteristics of the P, R, and T waves well (Figs 4a,b). Each steering-ECG R wave showed time-consistency with the respective R wave of the chest-ECG during the handling of the steering wheel, as well as while sitting still in the driver’s seat. Fig 5 shows a regression graph of steering-RR\( k \) to chest-RR\( k \) in the same subject as in Fig 4. Each element of \{steering-RR\( k \}\) corresponds to each one of \{chest-RR\( k \}\) in a regular 1-to-1 fashion by consecutively searching the R waves of the steering-electrocardiographic (ECG) and chest-ECG visually on a screen.

![Fig 4](image_url) Comparison of the electrocardiographic (ECG) recorded from a steering wheel (steering-ECG) with that from a chest lead (chest-ECG): (a) while stationary in the driver’s seat; (b) while handling the steering wheel. Each of the P, R, and T waves seen on the steering-ECG corresponds to its counterpart on the chest-ECG. The straight lines show time consistency between the respective peaks of the R waves of the steering-ECG and chest-ECG.

![Fig 5](image_url) Regression graph of the steering-RR\( k \) to chest-RR\( k \) in the same subject as in Fig 4. Each element of \{steering-RR\( k \}\) corresponds to each one of \{chest-RR\( k \}\) in a regular 1-to-1 fashion by consecutively searching the R waves of the steering-electrocardiographic (ECG) and chest-ECG visually on a screen.

**Software System**

Fig 6 shows the RR intervals from the steering-ECG and from the chest-ECG for the same subject as in Fig 4. When the driver moved the upper body abruptly, the baseline of the chest-ECG fluctuated so that, intermittently, the R waves could not be detected. Hence, rather long erroneous RR intervals sometimes appeared in the tachogram of the chest-ECG as well as in the steering-ECG. Longer RR intervals were observed more frequently in the tachogram of the steering-ECG. This occurred because the driver sometimes gripped only 1 side of the steering wheel with 1 hand. Because more long erroneous RR intervals were deleted in the steering-ECG than in the chest-ECG, the last index number...
Fig 6. RR intervals from the steering-electrocardiographic (ECG) and chest-ECG for the same subject as in Fig 4. \(I_n\): intervals of peaks of 2 successive QRS waves. \(\text{[RRI]}_n\): intervals regarded as RR intervals after the processing of outliers from \(I_n\) by the algorithm.

Fig 7. Comparison of the fluctuation from the steering-electrocardiographic (ECG) with that from chest-ECG for each parameter of the same subject as in Fig 4. Red lines show the moving averages of the blue lines. Mutual information values are 0.225, 0.223, 0.209, and 0.184 for m-HR, m-ln(LF), m-ln(HF), and m-ln(LF/HF). HR, heart rate; LF, low-frequency component (0.04–0.15 Hz); HF, high-frequency component (0.15–0.40 Hz); LF/HF, the ratio of LF to HF. ln(LF), ln(HF), and ln(LF/HF): natural logarithms of LF, HF, and LF/HF. m-HR, m-ln(LF), m-ln(HF), and m-ln(LF/HF): moving averages of HR, ln(LF), ln(HF), and ln(LF/HF).
of processed ln of the steering-ECG, \{steering-RRI\}, was smaller than that of the processed ln of the chest-ECG, \{chest-RRI\} (Fig 6). Hence, each element of \{steering-RRI\} did not correspond in a regular 1-to-1 fashion with that of \{chest-RRI\}, so that \{steering-RRI\} and \{chest-RRI\} could not be compared by the regression analysis.

Fig 7 shows that the fluctuation from the steering-ECG resembled that from the chest-ECG for each parameter in the same subject as in Fig 4. Particularly, most of the upslopes and downslopes of each parameter of the steering-ECG corresponded 1-to-1 with those of the chest-ECG. These findings were seen in the other subjects, when mutual information values were larger than 0.047. Fig 8 shows that the mutual information of each parameter was larger than 0.047, with 95% confidence interval, which indicated that the fluctuation of each parameter of the steering-ECG significantly resembled that of the chest-ECG. However, the mutual information of m-ln(HF) in 1 subject and that of \{steering-RRIn\} did not correspond 1-to-1 with that of \{chest-RRI\}, so that \{steering-RRIn\} and \{chest-RRI\} could not be compared by the regression analysis.

**Discussion**

The waves of P, Q, R, S, and T are generally visible clearly in a standard ECG during which the subject lies supine on a bed. In the present study, the waves of P, R, and T could be recorded clearly in the steering-ECG (Fig 4); in fact, \{steering-RRI\} was almost perfectly consistent with \{chest-RRI\} in all subjects. Similarly, ln(LF), ln(HF), and ln(LF/HF) of the steering-ECG were almost perfectly consistent with those of the chest-ECG. Hence, the first of our goals was achieved, using the following technical measures. Long, indifferent electrodes were installed in both sides of the steering wheel so that they would work without fail, even if the driver’s hands moved on the steering wheel. The electrodes installed into the steering wheel were made of plating to increase their electrical conductivity. A bandpass filter of 0.2–35 Hz was used for the steering-ECG, which is comparable to the generally used bandpass filter of an electrocardiograph. Hence, the P, R, and T waves of the steering-ECG closely resembled those of the chest-ECG. Small HF noise contaminated not only the baseline of the steering-ECG but also that of the chest-ECG (Fig 4), indicating that it is difficult to record a noise-free ECG in an automobile.

This contaminating noise resulted from alternating current, making the ST-segment of the ECG unclear. Generally, small P waves, flat T waves, and small, inverted T waves may be invisible by the contaminating noise. In order to detect ischemic attacks, namely, angina pectoris and acute myocardial infarction, it is necessary to eliminate that noise. We will endeavor to reduce noise in a further study.

After detecting the QRS waves by our algorithm shown in Fig 2, we measured the RR-intervals using a peak-detection algorithm. In the preliminary study, we examined the reliability of this algorithm by applying it to the ECG database of PhysioBank. It was applicable to the ECG of patients with abnormal Q waves in lead I, usually observed in broad anterior myocardial infarction or dilated cardiomyopathy (Fig 3) as well as to the ECG of normal subjects.

When a driver moved the upper body abruptly and/or gripped only 1 side of the steering wheel with a single hand, normal R waves could intermittently not be detected, and long erroneous RR intervals appeared. HRV mainly results from the pacemaker sinus node rhythm, which is under the control of the autonomic nervous system. Therefore, a time series including frequent noisy RR intervals, for example, in subjects at high risk of lethal arrhythmia who have frequently premature beats, atrial tachyarrhythmia such as atrial fibrillation, or pace maker implantation is unsuitable for HRV analysis. Practically, arrhythmias such as premature beats sometimes appear even in normal subjects, which causes erroneous RR intervals. Although the Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology published a report on the standard of measurement for HRV, no standard for how to deal with such noisy RR intervals was included. In subjects with frequent premature beats, the values of LF, HF, and LF/HF are rather inaccurate for data epochs including more premature beats. Thus, we presume that our method of dividing the data into 5 epochs with 50% overlap and ensemble averaging is useful for enhancing the confidence of these values, according to Welch’s method.

Overly long or short RR intervals were excluded as outliers: ln>MI+2SDI or <MI–2SDI. Consequently, approximately 5% of all the intervals ln were excluded. These outliers resulted from artifacts caused by abrupt body movement and/or gripping only 1 side of the steering wheel. More of these long erroneous RR intervals appeared in the steering-ECG than in the chest-ECG, and more outliers were excluded in the steering-ECG. The number of RR intervals was less in the steering-ECG than in the chest-ECG (Fig 6). Each element of \{steering-RRI\} did not correspond in a regular 1-to-1 fashion with that of \{chest-RRI\}, so that \{steering-RRI\} and \{chest-RRI\} could not be compared by the regression analysis. Hence, we needed to use the mutual information method as an alternative method of comparing the HRV of \{steering-RRI\} and \{chest-RRI\}.

We aimed to construct a reliable graph following fluctuation of autonomic nervous activity. The mutual information of each parameter was larger than 0.047, with 95% confidence interval, which indicated statistically that the fluctuation of each parameter of the steering-ECG significantly resembled that of the chest-ECG. In detail, all but 2 mutual information values were larger than 0.047: mutual information of m-ln(HF) in 1 subject and that of m-ln(LF/HF) in another was 0. When mutual information was 0, the fluctuations of the steering-ECG did not resemble the respective fluctuations of the chest-ECG, because the steering-ECG
was noisy from the frequent gripping of the steering wheel with 1 hand.

We succeeded in demonstrating a fluctuation in autonomic nervous activity from the steering-ECG, which was statistically consistent with that of the chest-ECG. It is possible for a driver to observe a fluctuation of sympathetic nervous activity by ln(LF/HF) and a fluctuation of parasympathetic nervous activity by ln(HF). Hence, drivers can detect their own autonomic stress continuously. Atrial or ventricular premature beats can be detected by the present algorithm. Feedback information to the driver about autonomic stress and the appearance of premature beats will improve safety in driving. Our system will open doors to new strategies to minimize driver risk by making available the relevant data during the actual process of driving.

Study Limitations

The observations were limited to those in normal subjects. We need to examine whether our system is appropriate for a wide variety of cases.

References