PERIODIC BLINK MEASURES USING DYNAMIC WINDOWING

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Artificial neural network (ANN) models are a common tool for cognitive state assessment. It is best if the inputs to the model are periodic. Typically, these inputs are extracted from physiological signals such as the electroencephalogram (EEG), electrocardiogram (ECG), electrooculogram (EOG), and others. Spectral measures derived from EEG data are periodic due to the signal processing. Features based on heart activity and respiration are quasi-periodic by nature. Features extracted from EOG, such as blink rate, can be especially non-periodic and can contain outliers. One approach to deal with this problem is to use static windows to compute average blink rate. This approach has some shortcomings. A new approach that uses dynamic windowing, filtering, and sampling is presented here. This new approach produces periodic data that are dynamic, adaptive to the individual, and well suited for ANN model use.

Being able to assess a person's cognitive state as it relates to stress and cognitive workload has great appeal in many domains. A high level of workload can have detrimental effects in real-world operations. For example, air traffic controllers should avoid exceeding a moderate level of workload because they have the responsibility of keeping airplane passengers safe (Brookings, Wilson, & Swain, 1996). Medical physicians performing lifesaving operations cannot afford to slip into a state of cognitive overload and risk harm to the patient. There are many other examples of when accurate cognitive state assessment is paramount.

One technique for performing a workload assessment is the use of artificial neural network (ANN) models. ANN models are biologically inspired computer programs designed to simulate the way in which the human processes information (Agatonovic-Kustrin & Beresford, 2000). Wilson (2003), for example, used ANNs and physiological measures to assess workload in a well-controlled laboratory task. Borghini, Astolfi, Vecchiato, Mattia, & Babiloni (2014) provides a review of research that use neurophysiological signals for workload assessment of aircraft pilots and car drivers. Physiological measures that are periodic are best suited for ANN models used for assessment. Specifically, the physiological inputs are regularly (e.g., one Hz) provided to the model.

The electroencephalogram (EEG) is an electrical signal associated with brain activity and is often used in ANNs for cognitive assessment. Typically, the EEG signals are processed using windows (i.e., four seconds with 75% overlap) to generate spectral measures. Because of the signal processing, the EEG measures are periodic.

The electrocardiogram (ECG) is an electrical signal associated with heart activity. The measures (heart rate and heat rate variability) determined from the ECG are quasi-periodic. Specifically, the heart beats are somewhat consistent, but are not perfectly regular.

The vertical electrooculogram (VEOG) can be used to detect eye blinks. Blink rate and blink duration have been shown to be sensitive to changes in workload (Hoepf et al., 2016) and are useful inputs to ANN models. However, blink rate is very non-periodic (Figure 1) and varies substantially between individuals. Instantaneous blink rate is computed by taking the inverse (reciprocal) of the time (period) between two consecutive blinks. The resulting value is multiplied by 60 to convert it to blinks per minute. As shown in Figure 1, instantaneous blink rate will not represent a long term average when double blinks occur. This 30 second window contains four blinks, corresponding to a blink rate of eight blinks per minute (BPM). The blinks occur at 7.6, 15.0, 20.7, and 21.5 seconds. The associated instantaneous blink rates for blinks 2, 3, and 4 are 8.12, 10.5, and 74.63 respectively. The

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blink rate for the fourth blink is an outlier. Because the instantaneous values are not periodic and may contain outliers, they are not well-suited for use in ANN models.

One approach to overcome these problems is to compute blink rate using static (i.e., fixed length) windows. This approach produces periodic data, but has potential pitfalls associated with lag and accuracy. A new approach using dynamic (i.e., varying length) windowing is presented that overcomes these pitfalls. This new approach is coupled with a filtering and sampling technique to produce periodic blink measures. Both the static and dynamic approaches rely on algorithms that can detect blinks based on eye activity.

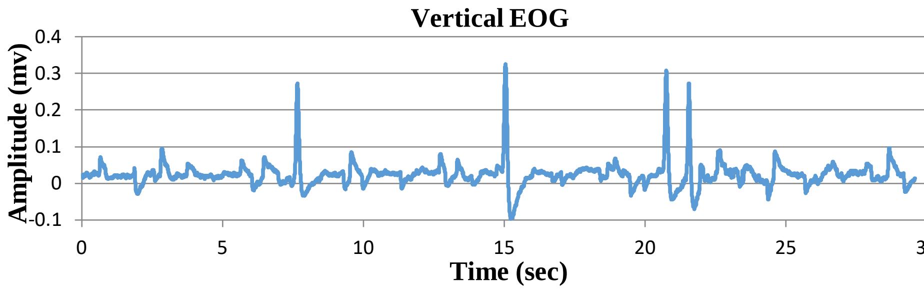

Figure 1. Vertical EOG data collected with blinks occurring at 7.6, 15.0, 20.7, and 21.5 seconds.

Background

Blink frequency and duration, can be acquired using various techniques. A common choice employs camera-based systems to measure eyelid position. The type of camera can vary, using technology such as laptop-based webcams (Krolak & Strumillo, 2011) or head-mounted eye trackers (Jiang, Tien, Huang, Zheng, & Atkins, 2012). These systems obtain video sequences, which can then be used in various algorithms to detect blinks.

Another common technique uses VEOG data to detect eye blinks (Pedrotti, Lei, Dzaack, & Rötting, 2011; Hu & Zheng, 2009). The VEOG data is processed by algorithms to detect blinks, commonly using thresholds and algorithm criteria. These thresholds can remain constant across trials (Ebrahim, Stolzmann, & Yang, 2013) or for the duration of the eye closure (Hu & Zheng, 2009). For a higher degree of specificity, the thresholds can be set specifically for each subject. An alternative route involves training the algorithm to adjust the detection parameters individually for each subject, allowing for more precision in eye blink detection (Kong & Wilson, 1998).

Because most camera-based detection methods depend on the stability of the subject's head for tracking position, they require the subject to remain still in an often unnatural position. In contrast, EOG recordings allow the participant to move around, since the electrodes are attached to the participant. This provides more reliable data, often with a higher sampling rate than camera-based methods.

Method

The intent of this paper is to present a new technique for generating periodic blink data using dynamic windowing. Therefore, the method sub-sections are presented concisely, with just enough detail to support the results section.

Participants

Ten individuals were recruited from the Midwest region to participate in this study. Eight participants were male and two were female, with an age range from 18-33 and a mean of 21.9. They read and signed the informed consent document before participating and were compensated for their time. All study procedures were reviewed and approved by the Air Force Research Laboratory Institutional Review Board.

Task Description

Two separate primary tasks (surveillance or tracking) were presented using a remotely piloted aircraft (RPA) simulation. A secondary communications task was also present.

Primary - Surveillance Task. The surveillance task required the participants to search a market place to find four high value targets (HVTs).

Primary - Tracking Task. The tracking task required participants to track HVTs travelling by motorcycle.

Secondary - Communications Task. A secondary task was presented concurrently with the primary tasks. Participants verbally answered a variety of mental math questions asked over a headset.

Apparatus

The VEOG data were acquired using two electrodes placed above and below the right eye. The VEOG data were sampled at 480 Hz using the Cleveland Medical Devices BioRadio 150. This device has hardware high pass filters with break frequencies of 0.5 Hz.

Procedure

Participants were brought into the laboratory for two days of task training and six days of data collection. During the course of the six data collection days, participants completed 24 surveillance trials and 24 tracking trials. VEOG acquisition hardware was present only on the six data collection sessions.

Static Window Approach

As reported earlier, researchers have used static windows to overcome the outlier issue associated with double blinks (Estepp & Christensen, 2015). In the current effort, static windows were explored. Blink rate was initially computed using a 30 second window with 29 second overlap. This approach deals well with the double blink outliers and produces periodic data. One concern with this approach is that the resulting blink rate measure will have a lag. This may not be ideal as an ANN input when a timely assessment is needed.

In an attempt to mitigate the lag concern, another approach was developed that uses a five second static window with four seconds of overlap. The output from this approach was often zero, quite granular, and was somewhat susceptible to the double blink effect. To address these issues, the output was low pass filtered. The filter was updated at a rate of 31.25 Hz so the output would transition smoothly from one value to the next. The output of the filter was sampled to generate periodic data.

The New Approach

The new approach is dependent on a blink detection algorithm that has a high degree of accuracy (Epling et al., 2015). The times of the detected blinks are buffered and supplied to the dynamic windowing algorithm to generate the periodic blink data (Figure 2). The dynamic windowing algorithm has three steps, including dynamic window calculation, filtering, and sampling.

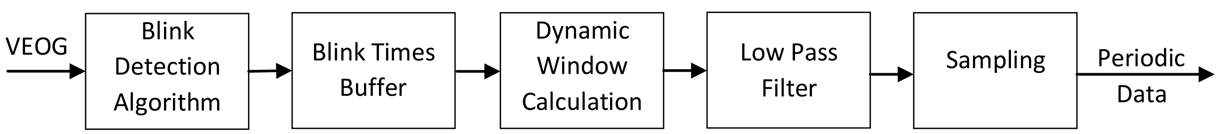

Figure 2. Steps in the periodic data calculation.

The dynamic window size (in seconds) is calculated based on the running average blink rate, which is computed by dividing the total number of blinks detected since the software was started is divided by the length of time the software has been running. The window size must be large enough to contain two blinks. This requirement (as opposed to one blink) was necessary to prevent several windows from having zero blinks in them. An individual with a blink rate of 12 BPM (an average of 5 seconds per blink) will have a window size of 10 seconds. The computed window size is limited to a maximum value of 30 seconds. The dynamic windowing approach results in window sizes that are adaptive between individuals, and dynamic within the individual.

The software that performs all of the calculations updates at 31.25 Hz. During each update, the dynamic window size is computed, the number of blinks in the window are counted, and the resulting blink rate is computed by dividing the count by the window size. The result is multiplied by 60 to convert the blink rate from blinks per second to blinks per minute (BPM). The blink rate is then processed by a first order Butterworth low pass filter with a cutoff frequency of 0.1 Hz. The output of the filter is sampled at regular intervals (i.e., one second) to produce the periodic blink data. Figure 3 shows instantaneous blink rate data that has been processed by the dynamic blink algorithm. The outlier (74.6 BPM) due to a double blink has been substantially reduced.

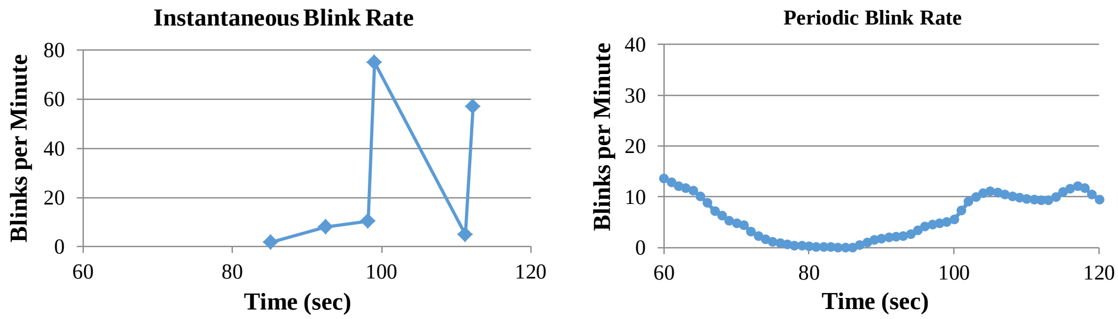

Figure 3. The left panel shows instantaneous blink rate produced by the blink detection algorithm. The right panel shows the same data after it has been processed by the dynamic windowing algorithm. The data in the right panel is sampled at 60 Hz.

Results

Actual blink rates were computed *post hoc* by dividing the number of blinks in an experimental trial by the length of the trial. This results in 24 values for each participant and task (surveillance & tracking). This serves as truth data for evaluating the dynamic blink rate data. The dynamic blink rate data were averaged across trials for each participant and task. Correlations were performed between the actual blink rates and the average dynamic blink rates. For the surveillance task, the correlations ranged from 0.91 to 1.0 with a mean of 0.97. For tracking, the range was from 0.97 to 1.0 with a mean of 0.99. These correlations indicate that the periodic blink rate based on dynamic windowing accurately reflects the actual blink rate. Figure 4 shows the reported correlations.

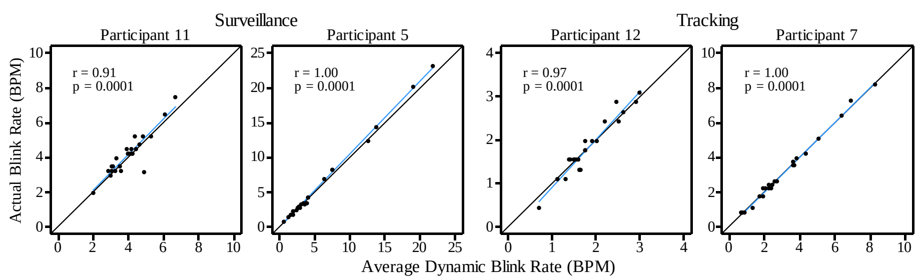

Figure 4. This figure shows the lowest and highest correlations between actual blink rate and average dynamic blink rate for the surveillance and tracking tasks. For surveillance, the lowest correlation is from participant 11 and the highest is from participant 5. For tracking, the lowest is from participant 12 and highest is from participant 7.

The instantaneous blink rate data were also averaged and correlated with the actual blink rate data. The correlations were lower than the correlations between average dynamic blink rate and actual blink rate. For the surveillance task, the correlations ranged from -0.2 to 0.89 with a mean of 0.5. For tracking, the range was from 0.02 to 0.93 with a mean of 0.63. These results indicate that instantaneous blink rate is inferior to dynamic blink rate because instantaneous blink rate contains huge outliers due to double blinks. Figure 5 shows examples of these correlations.

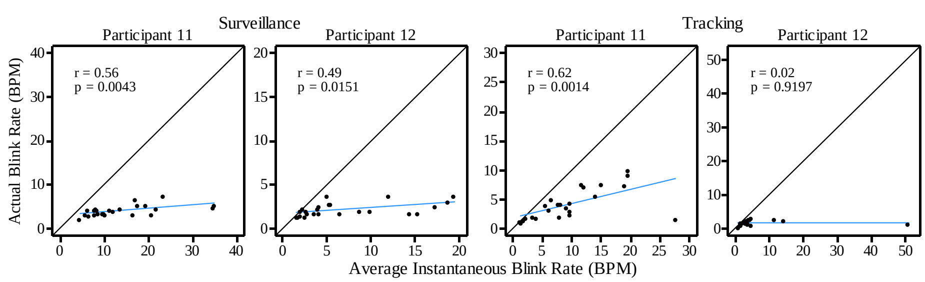

Figure 5. These examples show correlations between actual blink rates and average instantaneous blink rates.

The blink rate data from the two static windowing approaches were also averaged across trials and correlated with actual blink rate. The correlations for the 30 second window were generally high with the exception of participants with low blink rates. The correlations ranged from 0.75 to 0.99 with a mean of 0.86 for the surveillance task and 0.48 to 0.99 with a mean of 0.86 for the tracking task.

The correlations for the five second window were generally high, but were slightly lower than the 30 second window. The correlations ranged from 0.67 to 0.99 with a mean of 0.92 for the surveillance task, and 0.42 to 0.99 with a mean of 0.87 for the tracking task.

The above correlations are based on averages across trials. Additional insights are realized when the data are examined as a time series. Figure 6 shows time series data from a participant with a low blink rate (~3 BPM). The data from a static 30 second windowing approach closely matches the data from the dynamic windowing approach (left panel). Data from the five second windowing approach does not follow the data from dynamic windowing approach very closely (right panel), and appears to be "noisy."

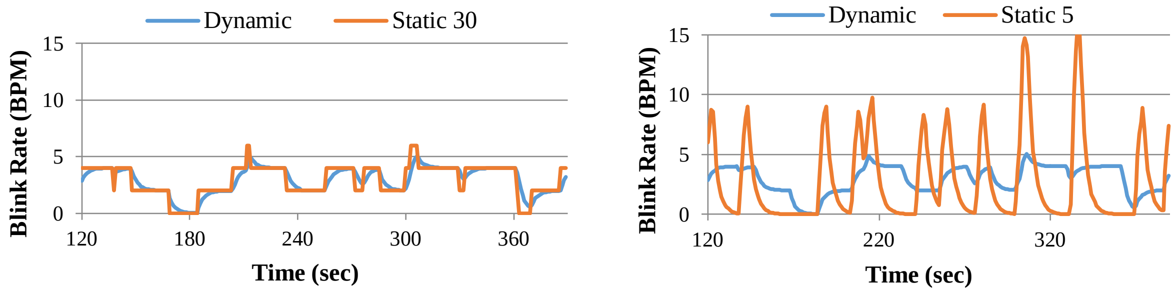

Figure 6. Time series data from a participant with a low blink rate (~3 BPM). Both panels have the periodic blink rate data computed using dynamic windows. The left panel includes blink rate computed using a static 30 second window, while the right panel includes data using a static five second window.

Figure 7 shows data from a participant with a high blink rate (~21 BPM). In this case, the five second window matches the dynamically windowed data better than the 30 second window. The two time series on the right panel (Figure 7) are nearly identical, making it nearly impossible to observe a difference.

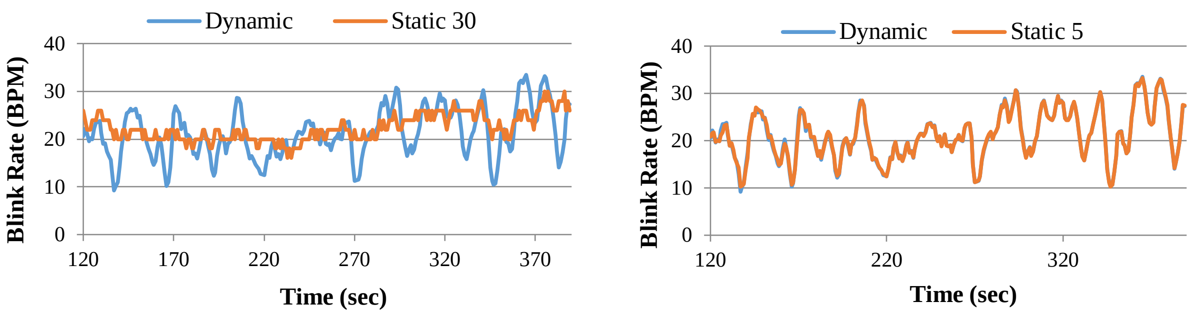

Figure 7. Time series data from a participant with a high blink rate (~21 BPM).

Discussion

The new method of generating periodic data using dynamic windowing is superior to static windowing because the window size is adaptive to the individual. This is in contrast to a one-size-fits-all approach. Figures 6 and 7 show that different static window sizes are needed dependent on the participants' blink rate. The new approach is also dynamic within an individual because the window size can change over time. The dynamic windowing algorithm is effective (Figure 3, right panel) in dealing with instantaneous outlier values due to double blinks. The filtering and sampling works well for creating periodic data.

The high correlations between actual blink rate and average dynamic blink rate indicate that these two quantities are measuring the same thing (i.e., blink rate). One advantage of the new dynamic blink rate approach is that the data is generated in real-time, whereas the actual blink rate is *post hoc*. Having periodic data available in real-time, with minimal lag and free from outliers, is optimal for use with ANN models.

One limitation of the current approach was in the calculation of the dynamic window size. Currently, it is based on rolling blink rate, which is computed from the time the software is started. Over a long period of time, the rolling blink rate becomes very stable and the dynamic aspect of the new approach is diminished. In future work, a long window (on the order of minutes) will be used to compute rolling blink rate to address this concern.

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