Behavior Research Methods, Instruments, & Computers
1998, 30 (4), 713-719

Program Abstracts/Algorithms

A new EOG-based eyeblink detection algorithm

XUAN KONG
Northern Illinois University, DeKalb, Illinois

and

GLENN F. WILSON
Air Force Research Laboratories, Wright-Patterson Air Force Base, Ohio

Accurate and efficient operator functional state classification and assessment based on physiological data have many important applications ranging from operator monitoring to interaction and control of human/machine systems. Eyeblink characteristics are frequently used as physiological indicators for this purpose. In this paper, we describe an efficient and robust eyeblink detection algorithm based on nonlinear analysis of the electrooculogram (EOG) signal. The performance of the algorithm was evaluated via data analysis results of several benchmark test sets in comparison with another eyeblink detection algorithm.

Eyeblinks are periodic closings and reopenings of the eyelid. The duration of the eyelid closure is used as the criterion to discriminate an eyeblink from an eye closure. An eyeblink closure duration is usually 300 msec and is more typically 200 msec or less. The electrooculogram (EOG) records changes in the electrical potentials between the cornea and retina as the eyelid movement occurs. The lid closing over the eye causes a difference in the corneal/retinal potential that is evident in the EOG (Stern & Dunham, 1990). Therefore, the EOG can be used to detect eyeblinks. In this paper, a new algorithm is described that automatically detects eyeblinks in the EOG.

There is a growing interest in exploring the information contained in eyelid movement patterns (i.e., eyeblinks). Tasks requiring high levels of visual demand have been found to reduce blinking. These tasks include visual tracking (Poulton & Gregory, 1952; Wilson, 1993), landing an airplane (Stern & Dunham, 1990; Wilson & Fisher, 1991), air traffic control (Brookings, Wilson & Swain, 1996), and reading (Stern & Dunham, 1990). Fatigue, on the other hand, may be associated with increased blinking (Stern, Boyer, & Schroeder, 1994). Several methods have been used to detect eyeblinks in the EOG (Stern & Dunham, 1990; Veltman & Gaillard, 1996). To monitor or assess such conditions when there are large quantities of data, it is desirable to develop automatic eyeblink detection algorithms. Since the EOG can be easily recorded, it provides a convenient method in which eyeblink events can be detected. However, this is not a trivial task, as eyeblink patterns vary significantly within and between subjects: Figure 1 shows EOG traces of four different eyeblinks from 1 subject, showing the variability. This variability justifies the need for developing EOG-based eyeblink detection algorithms that are robust to noise, artifacts, and intra- and intersubject variations.

Method

The proposed eyeblink detection algorithm first enhances relevant features in the EOG and then determines whether an EOG complex is an eyeblink or not via a composite matching score. First a nonlinear erosion filter is used to enhance troughs in the EOG signal that may be possible eyeblinks. Then a differentiation filter is used to reduce baseline drift. Finally, median and threshold filters are utilized to suppress noise in the EOG signal.

To determine whether an EOG complex corresponds to an eyeblink, features extracted from the preprocessed EOG are checked against reference values. The results of the evaluations of individual features are combined to form a composite score upon which a decision is made as to whether the EOG complex is an eyeblink or not.

Preprocessing of EOG. The most important EOG characteristic that distinguishes an eyeblink from other eye movements is the steep negative slope, which corresponds to the rapid eyelid closure. In order for an eyeblink algorithm to reliably detect such an event, a nonlinear erosion filter is first applied to the EOG signal $x[k]$ (Serra, 1982):

$$y[k] = \min\{x[k-E], x[k-E+1], \cdots, x[k], \cdots, x[k+E]\}, \quad (1)$$

where E is the order of the erosion filter. Unlike many linear filters, the erosion filter will not smooth the edges of the original signal (especially the leading negative slope). In fact, as can be seen from Figure 2b, the trough of the eyeblink waveform is actually enhanced. Another advantage of the erosion filter is that it can remove positive-going spike-like noise. The order E should be less than half of the expected eyeblink duration. For example, if the expected blink duration is 200 msec (10 samples with a sampling rate of 50 Hz), the order E should be less than five samples.

We thank reviewers for their comments, which helped in improving the quality of our paper. Correspondence should be addressed to X. Kong, Department of Electrical Engineering, Northern Illinois University, DeKalb, IL 60115 (e-mail: kong@ceet.niu.edu).

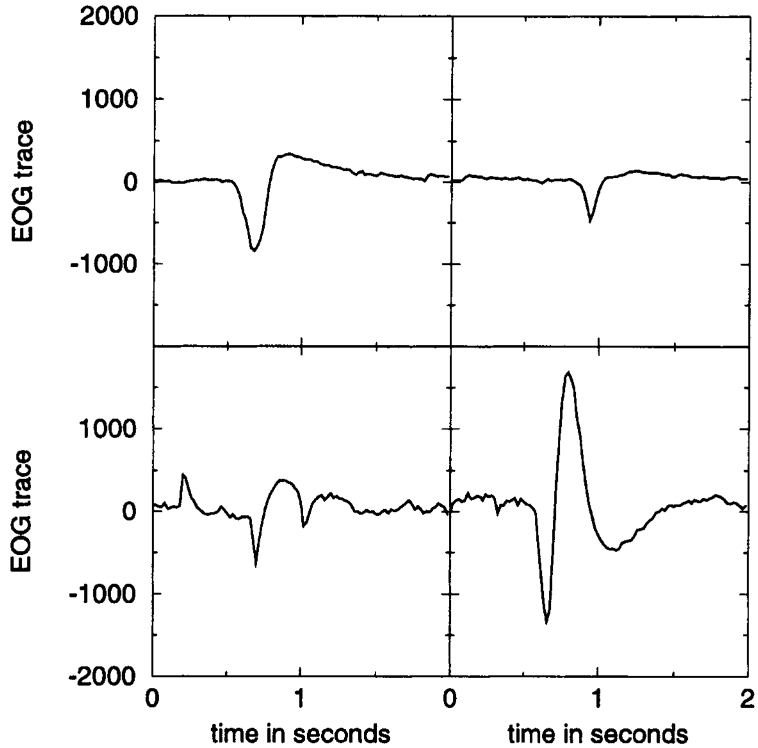

Figure 1. Sample electrooculogram (EOG) traces for four eyeblinks from the same subject. The figure demonstrates the large variations in eyeblinks and the need for robust eyeblink detection algorithms. The EOG signals were first filtered with cutoff frequencies at 0.1 and 40 Hz, and then they were sampled at 500 Hz initially. Vertical axis unit is arbitrary but consistent throughout the paper.

For applications where obtaining exact eyeblink durations is important, it should be remembered that the erosion filter expands both the negative and the positive slopes of an eyeblink complex outward by roughly E samples. Therefore, the eyeblink duration estimated on the basis of preprocessed EOG is approximately $2E/F_s$ sec longer (F_s denotes the sampling rate in Hertz).

Following the erosion filtering, the slopes of potential eyeblink waveforms are determined. Since an eyeblink is characterized as a large negative slope followed by a positive slope within a predefined time limit, a "low-noise" Lanczos differentiation filter introduced in Hamming (1989) is employed (see Figure 2c). The coefficients of an Nth order Lanczos differentiation filter are as follows:

$$h_k = -\frac{3k}{N(N+1)(2N+1)},$$
$$k = -N, -(N-1), \cdots, N-1, N. \quad (2)$$

Frequently, a first order differentiation filter is sufficient and has the familiar form of symmetric difference:

$$w[k] = \frac{1}{2}\left(y[k+1] - y[k-1]\right). \quad (3)$$

To reduce the effects of noise, characterized by small fluctuations around zero, a median filter is also used with the order of the median filter denoted as M [An Mth order median filter sorts $2M + 1$ samples and outputs the $(M + 1)$th sample value]. The median filter acts like a mean filter except that it preserves the sharp edges of the input. The order M should be less than a quarter of the expected eyeblink duration. Finally, a threshold filter is used to reduce the false alarm rate by zeroing out slope values near zero:

$$z[k] = \begin{cases} w[k] & |w[k]| \geq W \\ 0 & \text{otherwise.} \end{cases} \quad (4)$$

The resulting preprocessed EOG signal is shown in Figure 2d.

Eyeblink detection algorithm. Eyeblinks are determined from the EOG by identifying in $z[k]$ a negative peak followed by a positive peak within the desired time window. Of note are the areas under the negative and positive peaks in the processed EOG signal $z[k]$ that correspond to the magnitudes of the negative and positive slopes in the original EOG signal $x[k]$, and the peak positions roughly correspond to the midpoints of eyelid closure and reopening that define the eyeblink duration (Veltman & Gaillard, 1996).

Pseudocodes of the new algorithm are listed in Figure 3. The algorithm was implemented in MATLAB and evaluated on a PC system.[1] The EOG data used were sampled at 50 Hz.

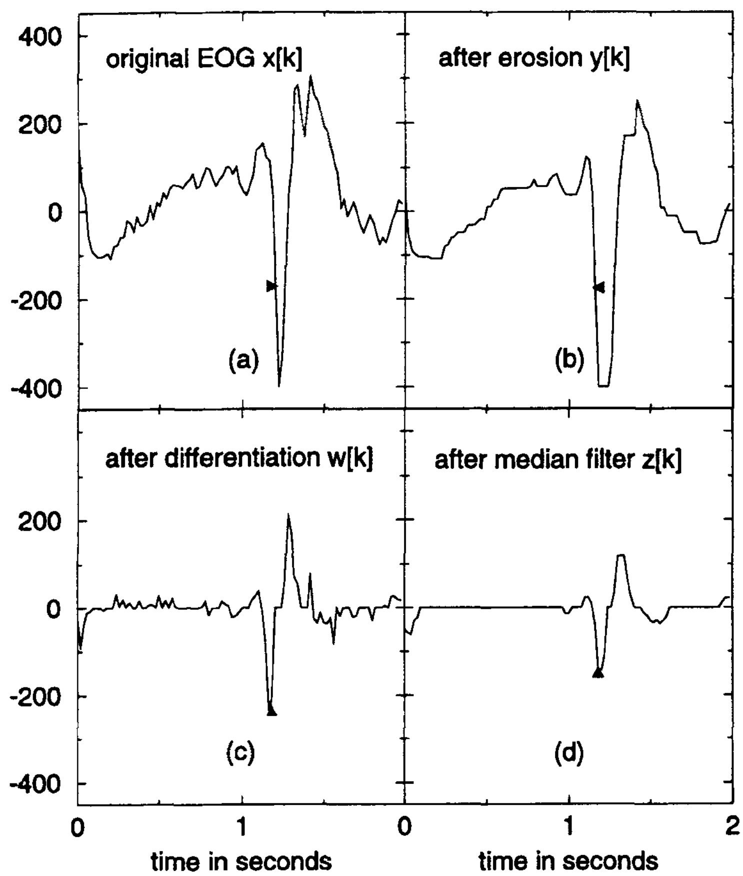

Figure 2. Intermediate electrooculogram (EOG) preprocessing results of the new eyeblink detection algorithm.

There are two modes under which the eyeblink detection algorithm can operate: training mode and detection mode. A flag is used to allow the algorithm to switch automatically from the training mode to the detection mode after the parameters are learned and adapted to the eyeblink patterns of a given subject.

In the training mode, the algorithm uses default parameter settings (e.g., predetermined averaged blink duration, slope sizes, interblink duration) to perform eyeblink detection. The algorithm then does a simple statistical analysis (mean and variance) of the eyeblink detection results. The algorithm automatically adjusts the detection parameters to provide a better fit of the eyeblink characteristics of the subject under study. The algorithm then repeats the eyeblink detection (with the new parameters) and continues the parameter updating process until the parameters converge or the number of iterations exceeds a predetermined value. Our experience suggests that the learning process converges in fewer than five iterations, and the entire training process is completed without any operator intervention.

In the detection mode, the algorithm first uses the erosion filter to enhance the eyeblink features and subjects the signal to differentiation (and thresholding) in order to minimize the effects of baseline drift. The algorithm then searches for a sequence of a negative slope followed by a positive slope. Once a sequence is detected, the following parameters are evaluated: blink duration, negative and positive slope sizes, and interblink interval. A composite matching score is generated on the basis of these features. The EOG complex is then classified as a blink, a possible blink, or a nonblink, depending on the composite score value.

The time difference between the negative and positive peaks of the preprocessed EOG complex determines the eyeblink duration. This is in general agreement with the commonly used half-amplitude definition with respect to the original EOG complex. Figure 2 is used to illustrate this correspondence: The half-amplitude point (as marked by a triangle) in the original EOG is the midpoint of the negative slope. When the EOG signal is differentiated, this negative slope is represented by the trough in $w[k]$ (Figure 2c), and the bottom of the trough is approximately the midpoint of this slope, as indicated by the triangles. Similarly, the correspondence between the midpoint of the positive slope in the original EOG $x[k]$ and

```
Algorithm Initialization
WHILE more data to process DO
    Pre-processing:
        erosion filtering
        differentiation filtering
        median filtering
    IF a negative slope followed by a positive slope
        continue to process the data
    ELSE
        process next data point
    ENDIF
    Feature Evaluation:
        blink duration matching
        negative slope size matching
        positive slope size matching
        inter-blink distance matching
    IF features satisfy blink criteria
        mark data as a small or regular blink accordingly
    ELSE
        process next data point
    ENDIF
ENDWHILE
```

Figure 3. Pseudocode for the new eyeblink detection algorithm (detection mode).

the positive peak of the preprocessed EOG $w[k]$ can be established.

Although the correspondence between the new peak definition and the traditional half-amplitude definition may not be exact in some blink EOG complexes, the new approach does provide unambiguous marking of eyelid closure and reopening. The new definition also permits a better detection of eyeblinks during up-going eye movements, since the EOG signal level after the blink is often less than half the level it is before the blink (thus no eyelid opening can be detected using the half-amplitude concept).

Once the blink duration is obtained, it is compared with the desired average value $D_{standard}$ obtained during the learning mode for the subject. If the blink duration of the EOG complex is different from the standard, the

Table 1
Performance Comparison of WAM System and New Eyeblink Detection Algorithm With Respect to Standard Expert II

EOG Segment	Total Blinks	WAM System Miss (%)	WAM System False (%)	WAM System Training Data	New Algorithm Miss (%)	New Algorithm False (%)	New Algorithm Training Data
grc	29	3	17	100 sec	0	10	100 sec
grc1	31	6	10	grc training result	3	6	grc training result
grc2	9	0	66	grc training result	0	44	grc training result
grc3	10	0	40	grc training result	0	10	grc training result
the1	85	4	25	100 sec	7	16	100 sec
the2	131	7	44	120 sec*	5	18	the1 training result

*The WAM system eyeblink detection error becomes extremely high with the training result for "the1," so the WAM system was trained again on the basis of the new segment, "the2."

matching score for the EOG complex is discounted. For example, the following scheme reduces the matching score for the EOG complex on the basis of the blink duration estimate D_{actual}:

IF $|D_{actual} - D_{standard}| \leq \sigma_{standard}$
matching score = 1.0

ELSE IF $D_{actual} > D_{standard}$
matching score = $(D_{max} - D_{actual})/(D_{max} - D_{standard})$

ENDIF,

where D_{max} is the maximum allowable blink duration and $\sigma_{standard}$ is the standard deviation of the eyeblink durations estimated during the learning mode.

Recall that the preprocessed EOG ($z[k]$ in Figure 2) is the result of the first order derivative of the original EOG signal $x[k]$. Thus the desired large size and steep slope features for the negative peak in the original EOG require both the total area and the averaged area per sample for the trough in the preprocessed EOG to exceed certain threshold values. If the desired values are not reached, the corresponding matching score is reduced accordingly. The positive slope matching score is similarly determined. Finally, the matching score is modified on the basis of the time difference between the current complex and the preceding eyeblink if a maximum allowable blink frequency is specified.

One important feature of this algorithm is that it uses a soft-decision process to calculate the likelihood of an EOG complex being a blink or nonblink on the basis of all the features, instead of just accepting or rejecting the EOG complex outright on the basis of any single feature. The composite score is reached only after all relevant features are considered. With this approach, a wide variety of the eyeblink patterns can be accommodated with a single criterion set.

Another advantage of using the composite score is that one can classify events as blinks, small blinks, possible blinks, or nonblinks, much like an expert might do when inspecting the EOG traces. This classification scheme provides a richer set of information for the decision process that follows. For example, eyeblink rate is an important factor in mental workload assessment. The assessment accuracy may be improved by taking into consideration more precise descriptions of the eye movements like small blinks and regular blinks.

The computational complexity of the eyeblink detection algorithm is given as follows (per sample point):

Operation	Number of Operations
Multiplication	15
Addition	14
Logic comparison	$11 + 2E + (2M + 1)\log_2(2M + 1)$

Given the speed of 486 or 586 PCs, the algorithm can easily process the EOG using only a small fraction of the computing resources. The current MATLAB implementation on a 486/100 MHz PC processes the EOG data four times faster than real time, even with extensive graphic displays.

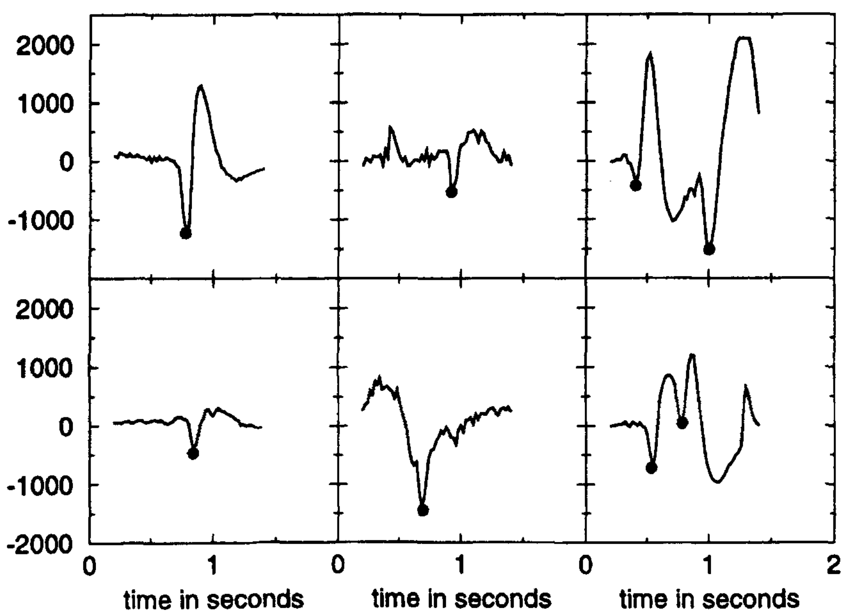

Figure 4. Sample electrooculogram (EOG) segments correctly classified as eyeblinks by the new algorithm using one set of parameter settings. Solid circles indicate the eyeblink events.

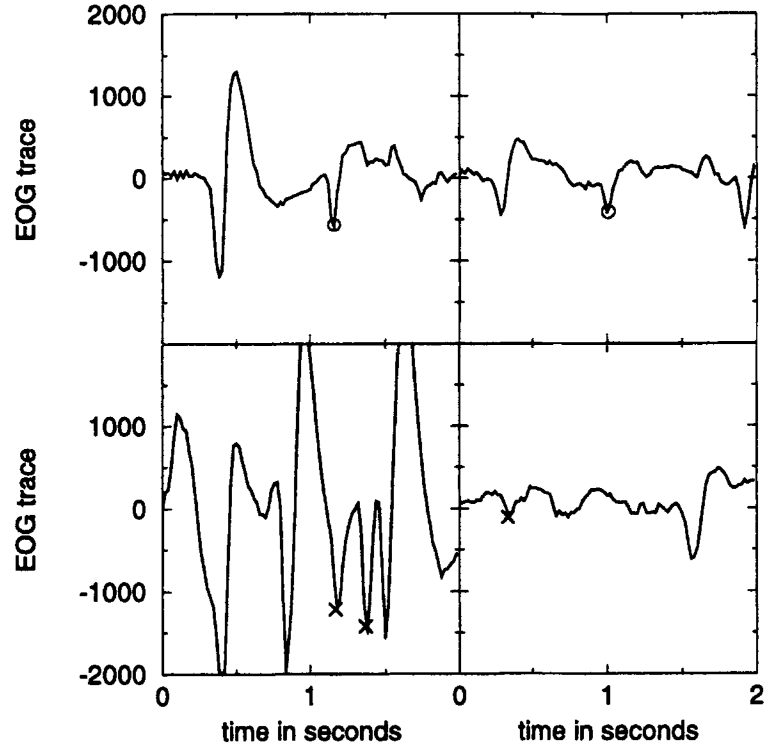

Figure 5. Sample electrooculogram (EOG) segments not correctly classified by the new algorithm using the same parameters as in Figure 4. Open circles indicate the missed eyeblinks and crosses indicate the false detections.

Data analysis. To evaluate the performance of the eyeblink detection algorithm, six previously recorded EOG segments from 2 subjects (grc and the) were analyzed. The detection accuracy is determined by comparing the algorithm detection results with a human expert's judgment and performance of the workload assessment monitoring (WAM) system.[2] The WAM system detects blinks using an algorithm that detects a negative slope followed by a positive slope. The slopes, the troughs, and the peaks of both the negative and the positive slopes must fall within the user-specified ranges. The criteria for the slopes and peak amplitudes are defined interactively by the user for each subject's data. Typically a human expert visually edits the WAM-selected blinks and adjusts the detection parameters until as many blinks as possible are correctly identified with as few false detections as possible. The usual procedure is to establish the criterion parameters before an experiment begins and to apply those parameters throughout the entire experiment. However, the shape of the blinks may change during an experiment, thus decreasing detection accuracy and requiring the establishment of new parameters for these data sets. Examples of data segments that would require resetting of the detection parameters can be seen in Table 1 (the1 and the2). Please note that data sets "the1" and "the2" were very difficult to analyze since the subject was instructed to purposely create artifacts such as excessive head movement, squinting, talking, swallowing, and horizontal eye movement during the recording. A sample collection of the eyeblinks correctly identified by the new algorithm is plotted in Figure 4.

To obtain the results in Table 1, both detection algorithms were trained on the initial data segment of the EOG file. During training, the WAM system required that the human expert manipulate the parameter settings manually while the training of the new eyeblink detection algorithm was done automatically. Using the preprogrammed algorithm to define eyeblink patterns reduced the subjective variations associated with human experts.

As shown in Table 1, the performance of the new algorithm was significantly better than that of the WAM system. Table 1 contains eyeblink detection results for six sets of EOG data from 2 subjects. The data sets contain many undesired artifacts such as head movement, squinting, talking, and swallowing. A comparison study based on these test data shows the robustness of the new algorithm to artifacts and its superiority over the WAM system as measured by the eyeblink detection accuracy. The new algorithm is expected to perform much better when normal EOG recordings are used. Figure 5 presents a few instances of missed eyeblinks and false detections that the current algorithm produces. However, detection accuracy could be increased by refining the algorithm.

All the results reported here use EOG data sampled at 50 Hz. Additional tests of the algorithm were conducted on EOG data sampled at higher frequencies (e.g., 500 Hz), and the algorithm accuracy rates remained the same. Processing EOG data sampled at a higher frequency yields a higher resolution for blink duration measure, and it also increases the number of computations per second. Processing EOG data with sampling frequencies lower than 50 Hz is not recommended because it compromises the ability of the algorithm to distinguish two closely spaced eyeblink events.

Conclusions

The new eyeblink detection algorithm is superior in at least the following four aspects when compared with the existing eyeblink detection algorithm used by the WAM system:

1. *Automatic training.* No human expert intervention is needed in the training phase. This feature allows real-time operation of the eyeblink detection process and maintains the consistency of the eyeblink detection criteria. The standardization of eyeblink patterns allows objective and consistent evaluations of various tasks and processes based on the eyeblink events detected.

2. *Intrasubject invariability.* Data analysis results suggest that the new algorithm is more robust to intrasubject eyeblink pattern variability. The new detection algorithm needs to be trained only once for each subject, and then it can accurately detect eyeblinks from any EOG measurements made for that subject with the same electrodes.

3. *Robust to artifacts.* The new algorithm incorporates nonlinear signal processing methods to reduce the effects of artifacts and recording noise. Analysis of results confirms the effectiveness of data preprocessing.

4. *Precise description.* The new algorithm assigns a likelihood value to each possible eyeblink event. This classification scheme is parallel to the judgment of an expert and thus makes it possible to label each eyeblink event (e.g., blink, small blink, possible blink) more precisely.

REFERENCES

Brookings, J. B., Wilson, G. F., & Swain, C. R. (1996). Psychophysiological responses to changes in workload during simulated air traffic control. *Biological Psychology*, **42**, 361-378.

Hamming, R. W. (1989). *Digital filters* (3rd ed.). Englewood Cliffs, NJ: Prentice-Hall.

Poulton, E. C., & Gregory, R. L. (1952). Blinking during visual tracking. *Quarterly Journal of Experimental Psychology*, **4**, 57-65.

Serra, J. (1982). *Image analysis and mathematical morphology.* New York: Academic Press.

Stern, J. A., Boyer, D. & Schroeder, D. (1994). Blink rate: A possible measure of fatigue. *Human Factors*, **36**, 285-297.

Stern, J. [A.], & Dunham, D. (1990). The ocular system. In J. Cacioppo & L. Tassinary (Eds.), *Principles of psychophysiology* (pp. 513-553). New York: Cambridge University Press.

Veltman, J. A., & Gaillard, A. W. K. (1996). Psychological indices of workload in a simulated flight task. *Biological Psychology*, **42**, 323-342.

Wilson, G. F. (1993). Air-to-ground training mission: A psychophysiological workload analysis. *Ergonomics*, **36**, 1071-1087.

Wilson, G. F., & Fisher, F. (1991). The use of cardiac and eye blink measures to determine flight segment in F4 crews. *Aviation, Space & Environmental Medicine*, **62**, 959-962.

NOTES

1. The MATLAB codes can be obtained from Glenn F. Wilson, USAF Air Force Research Laboratories, AFRL/HECP, 2255 H Street, Wright-Patterson AFB, OH 45433-7022.

2. Workload assessment monitoring system, USAF Armstrong Laboratory.

(Manuscript received March 14, 1997;
revision accepted for publication July 25, 1997.)