Image-based Open/Closed Eye Status Determination for Embedded System

John Paquet III, Andrew Rosenberg, Rory Makuch, Jiang Wu, Ph.D., Ying Sun, Ph.D.
Department of Electrical, Computer and Biomedical Engineering, University of Rhode Island
Kingston, Rhode Island, USA
Correspondence email: yingsun@uri.edu

***Abstract*—In this paper, we propose a simple SVM, or support vector machine, classifier-based algorithm for determining whether eyes are open or closed in images. Due to its computational simplicity, it can be implemented on embedded systems, such as the Blackfin Low-Power Imaging Platform (BLIP) by Analog Devices, Inc. This design provides an inexpensive and practical solution to drowsiness detection functionality in applications such as assistive devices for vehicle drivers or machinery operators.**

Keywords—eye status; image processing; machine learning; classifier; drowsiness detection; embedded systems

I. Introduction

Drowsiness detection plays an important role in advanced driver assistance systems (ADAS) in the latest vehicles by providing drivers fatigue information to avoid falling asleep while driving. Many alerting methods have been proposed based on a variety of information, including biomedical signals, driver behavior, stereo cameras, and IR cameras. Lately, low-cost video-based detection is receiving more and more attention [5]. Most of the reported research in this area requires computation-intensive eye/pupil shape recognition, such as the Haar Cascade Classifier and Camshift algorithms used to obtain eye blink detection [3]. In this paper, we propose a simple histogram-based SVM classifier for open/closed eye status determination targeted at less demanding computing platforms, such as the BLIP DSP board by Analog Devices.

The BLIP is a low-power, low-cost embedded computer vision board that is capable of many real-time video sensing applications, such as room occupancy determination and motion tracking. Images and videos captured by the BLIP camera can be analyzed in real time, and the USB ports on the board allow for external output video storage or display. Previous work at URI [2] with the BLIP includes using frame subtraction to monitor the activity of the elderly by identifying changes in consecutive images, thus determining whether an individual has moved and also to what degree the motion has occurred. In this research work, we continue using the same platform, but with the purpose of determining whether eyes are open or closed.

II. Methods

A. Algorithm

Open/closed eye status determination can be considered as a classification problem, and different machine learning classification methods can be utilized. They all share the same procedure: sample data collection, feature extraction, coefficient training, and prediction. For this particular research, after many experiments, histogram features and an SVM classifier are chosen.

Fig. 1 shows the process of feature extraction. The captured eye images are first converted to grayscale images if they are only available in RGB or YUV format, since the luminance components include the most important information about eye status. To eliminate the variation in image exposure, pixel-wise maximum/minimum normalization is applied to each grayscale image. In reality, if the exposure setting of the camera is fixed, this step can be omitted.

An 8-bin histogram is then computed across each grayscale image. The number of bins is chosen to be 8 so that the histogram can be easily computed by no more than 3-step shifting of the 8-bit pixel value while providing sufficient information for classification afterwards. The first 4 bins of the histogram are chosen to be the 4-dimensional feature vector. As a standard procedure, the feature vector is normalized to a standardized data set

$$f_{ij} = (h_{ij} - \mu_i)/\sigma_i, \quad i = 1,2,3,4 \text{ and } j = 0,1,\cdots N-1 \qquad (1)$$

with a mean of zero and a standard deviation of one, where h_{ij} is the i^{th} feature of sample j and μ_i, σ_i are the mean and standard deviation, respectively, of the i^{th} feature of the N samples. In order to train the classifier, eye images are captured and labeled as open or closed, and the collection of images is then split into a training set and a test set. The training set is used to find the classifier model coefficients, and the test set is used to assess the effectiveness of the model and coefficients.

A standard SVM classifier engine can be readily applied to the feature vectors of the captured sample images. The learned model coefficients are then used for model prediction of the real-time eye images to provide automatic eye status determination.

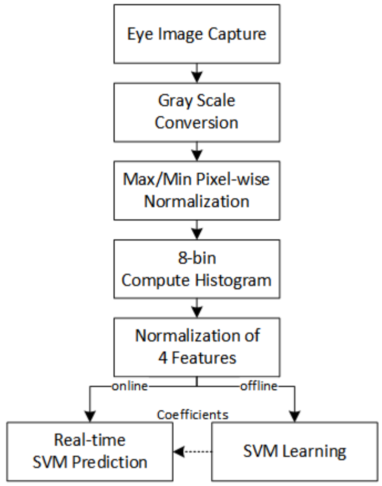

Fig. 1. Feature Extraction Diagram

B. Hardware

The BLIP board is used to capture eye images and will later perform real-time prediction. Thanks to its low primary voltage domains of 3.2, 1.8, and 1.1 volts and its petite 2.5-inch by 3.5-inch dimensions, this embedded platform can be easily integrated into many systems. To access the on-board Aptina ASX340AT imaging sensor, which captures 640-pixel by 480-pixel images at 30 frames per second, AD Vision Sensor Controller 1.0.1 is installed on a PC running several other Analog Devices programs for development and demonstration purposes.

III. RESULTS

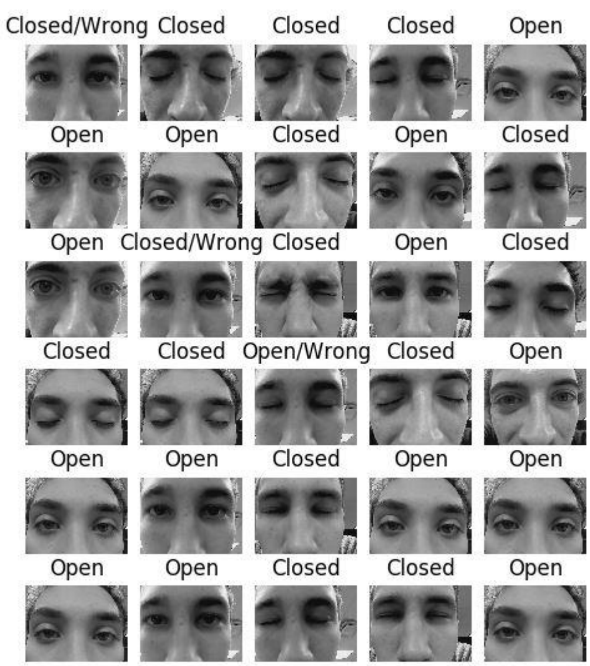

Fig. 2. 30 grayscale images tested against the machine learning algorithm. The eye status of 27 of the 30 images was successfully determined.

The built-in camera of the BLIP board was used for sample eye image collection. The images are labeled and processed by a Python script for normalization and feature extraction. Then, the SVM model provided by the Python machine learning package Scikit-learn is used for model training and verification. In our test, 152 images of three different individuals with open and closed eyes were captured for coefficient learning: 122 for the training set and 30 for the test set. Fig. 2 shows the classification results for the test images. A detection rate of 90% or better is achieved.

IV. DISCUSSION

The next major step of the project is to program the BLIP microprocessor. The BLIP embedded system will have an SVM prediction function implemented and executed on real-time eye images, based on the already-learned model coefficients. The code for the embedded system will be developed in C with CrossCore Embedded Studio 2.1.0, an integrated development environment made by Analog Devices. Also, the image populations to train the machine learning algorithm and to test it should be extended and further diversified to increase the algorithm's robustness and further verify its functionality and efficacy. Future work includes using the system to alert tired drivers through determining if the eyes have been closed for a duration longer than that of a typical blink or if the rate of blinking is below normal. In addition, the BLIP system, by differentiating intentional eye blinking from involuntary blinking, could allow for easier control of devices for people suffering from spinal cord injuries.

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