Robust Eyelid Tracking for Fatigue Detection

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Introduction

Fatigue from chronic partial sleep deprivation, circadian misalignment, and work overload is a risk factor for people driving vehicles or performing critical tasks. There is a need for techniques that objectively and unobtrusively identify the presence of fatigue on-line.

Previous researches have found that tracking slow eyelid closures (referred to as PERCLOS) is one of the most reliable ways to detect lapses of attention during critical tasks. We build the Optical Computer Recognition (OCR) system which can monitor alertness in real time providing an early detection of fatigue. By tracking human faces and measuring PERCLOS using inexpensive camera equipment, our system offers a completely unobtrusive way to achieve this requirement.

System Overview

We have developed a system that is capable of real-time tracking of facial landmarks (e.g., eyes, eyebrows, nose, mouth), using statistical deformable models and the KLT tracker. We use the tracked positions of the eyes as a basis for our eye segmentation algorithm, and then further refine it by fitting geometrical templates to the map of pixel-wise likelihood. An expectation maximization (EM) algorithm is used to cluster the pixels in HSV color space, using the first few tracked frames.

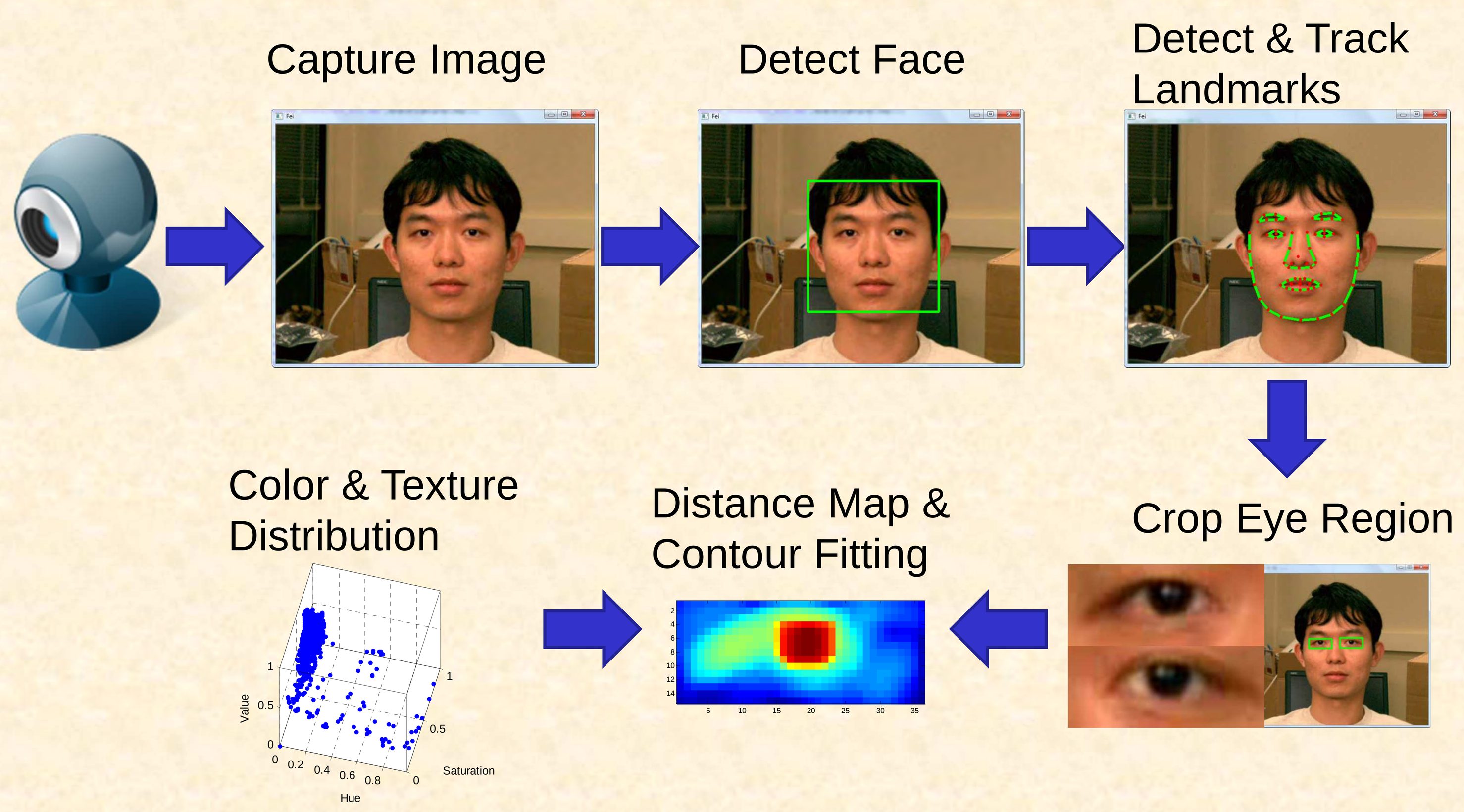
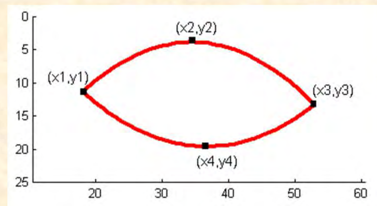


Fig 1. System flowchart

Eyelid Fitting

We define the eye template as two parabolic sections $y_i = a_i x^2 + b_i x + c_i, (i = 1,2)$ The parameters are then optimized to best fit the pixel-wise likelihood by using gradient descent method. Denote $\theta_i = [a_i, b_i, c_i]^T$.

- The likelihood is



$$L(\theta|I) = L(\theta_1|I) + L(\theta_2|I)$$

$$= \int_{x=x_1}^{x_2} \int_{y=y_1(x)}^{y_2(x)} s(x,y)\,dy\,dx$$

- Then

$$\frac{\partial L}{\partial \theta_i} L = (-1)^i \begin{bmatrix} \int_{x_1}^{x_2} y_i(x) x^2 dx \\ \int_{x_1}^{x_2} y_i(x) x dx \\ \int_{x_1}^{x_2} y_i(x) dx \end{bmatrix}, (i = 1,2)$$

- And

$$\frac{\partial L}{\partial y_j} = \sum_{i=1}^{2} \frac{\partial L}{\partial \theta_i} \cdot \frac{\partial \theta_i}{\partial y_j}, \text{ and } \frac{\partial L}{\partial x_j} = \sum_{i=1}^{2} \frac{\partial L}{\partial \theta_i} \cdot \frac{\partial \theta_i}{\partial x_j}$$

- The likelihood is maximized by gradient descent.

Pixel-wise Distance Map

We perform an expectation maximization algorithm to find skin color distribution in HSV color space.

ALG: Find Skin Color Distribution

1. Put all pixels inside the bounding boxes of eyes in Set P.
2. Repeat
3. Compute Gaussian distribution (μ, σ) of pixels in P.
4. For all pixels in eye region, compute the probability to $N(\mu, \sigma)$.
6. Take 50% pixels with largest probability and update P.
7. Until (μ, σ) converges.

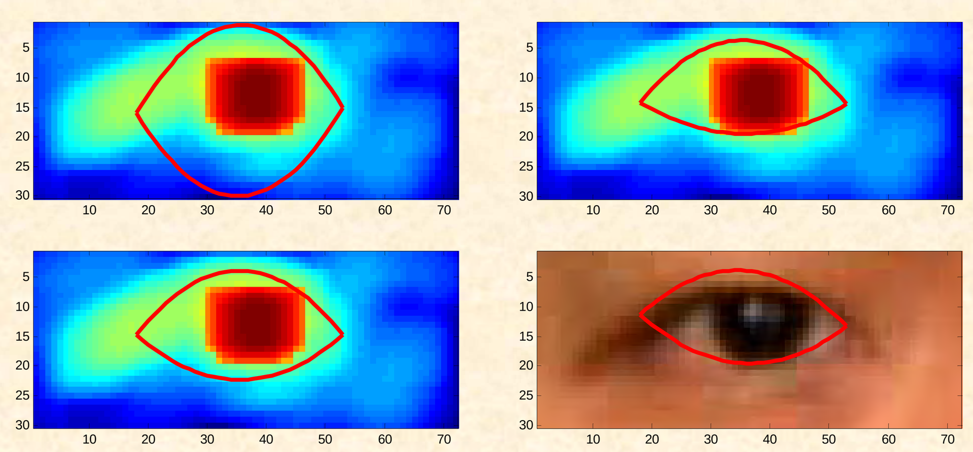


Fig 2. Eye contour fitting procedure

Experimental Results

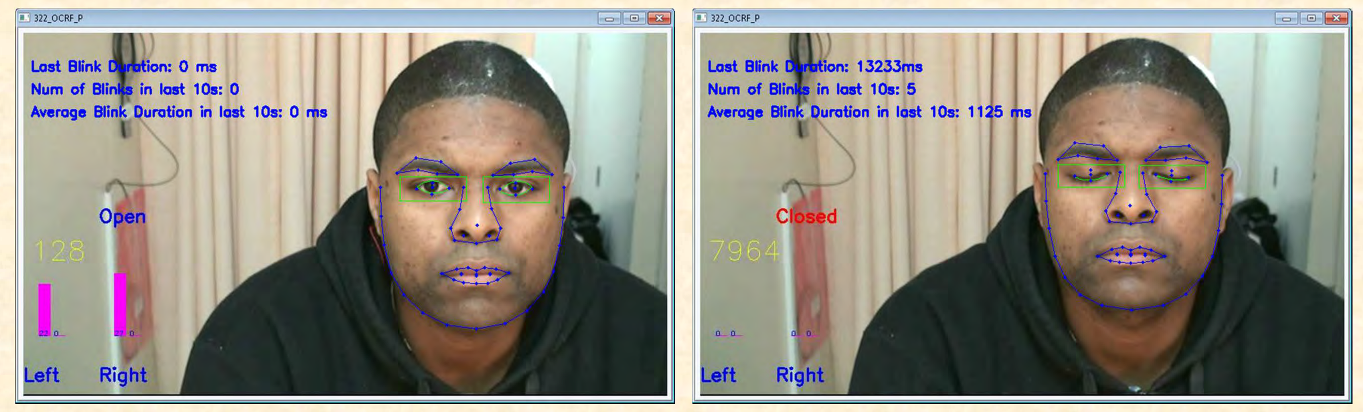


Fig 3. Examples of the eyelid fitting, open eyes v.s. closed eyes

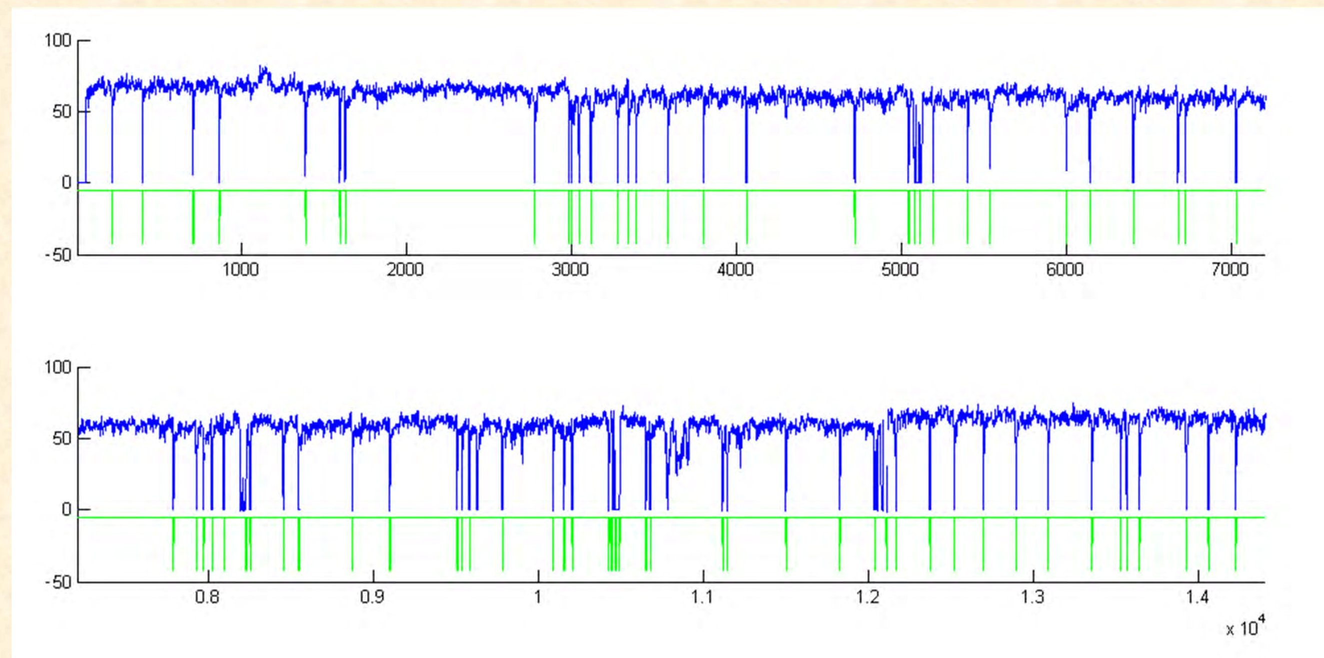


Fig 4. Eye closure scores evaluated by our system (blue) and blinks labeled by human (green), on a video clip of 8 minutes when the subject is alert.

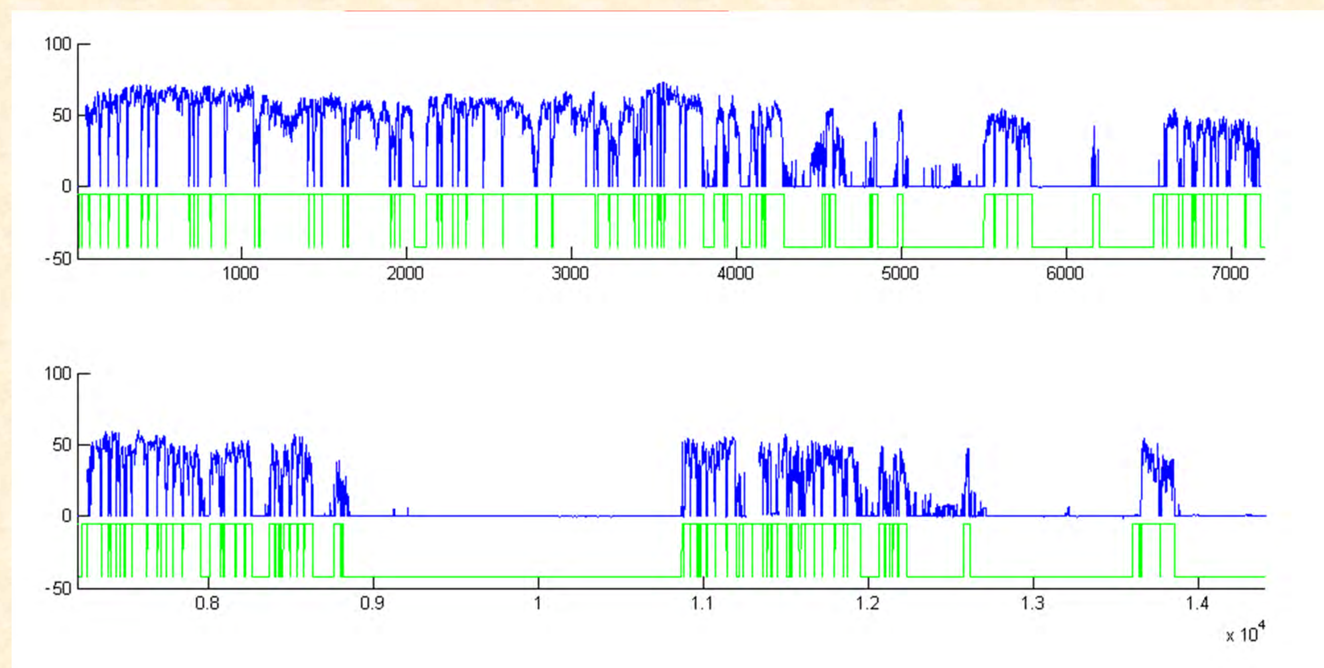


Fig 5. Eye closure scores evaluated by our system (blue) and blinks labeled by human (green), on a video clip of 8 minutes when the subject is drowsy. Two typical characteristics of fatigue, frequent blinking and long eye closure are illustrated.

	Hit Rate	False Detection Rate
Alert	94.0%	7.3%
Drowsy	87.3%	10.6%

Table 1. Accuracy of blink detection