Development of Optical Computer Recognition (OCR) for Monitoring Fatigue in Space

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Introduction

Fatigue from chronic partial sleep deprivation, circadian misalignment, and work overload is a risk factor for astronaut cognitive performance in space flight. There is a need for techniques that objectively and unobtrusively identify the presence of fatigue on-line, when astronauts are performing critical tasks in space.

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.

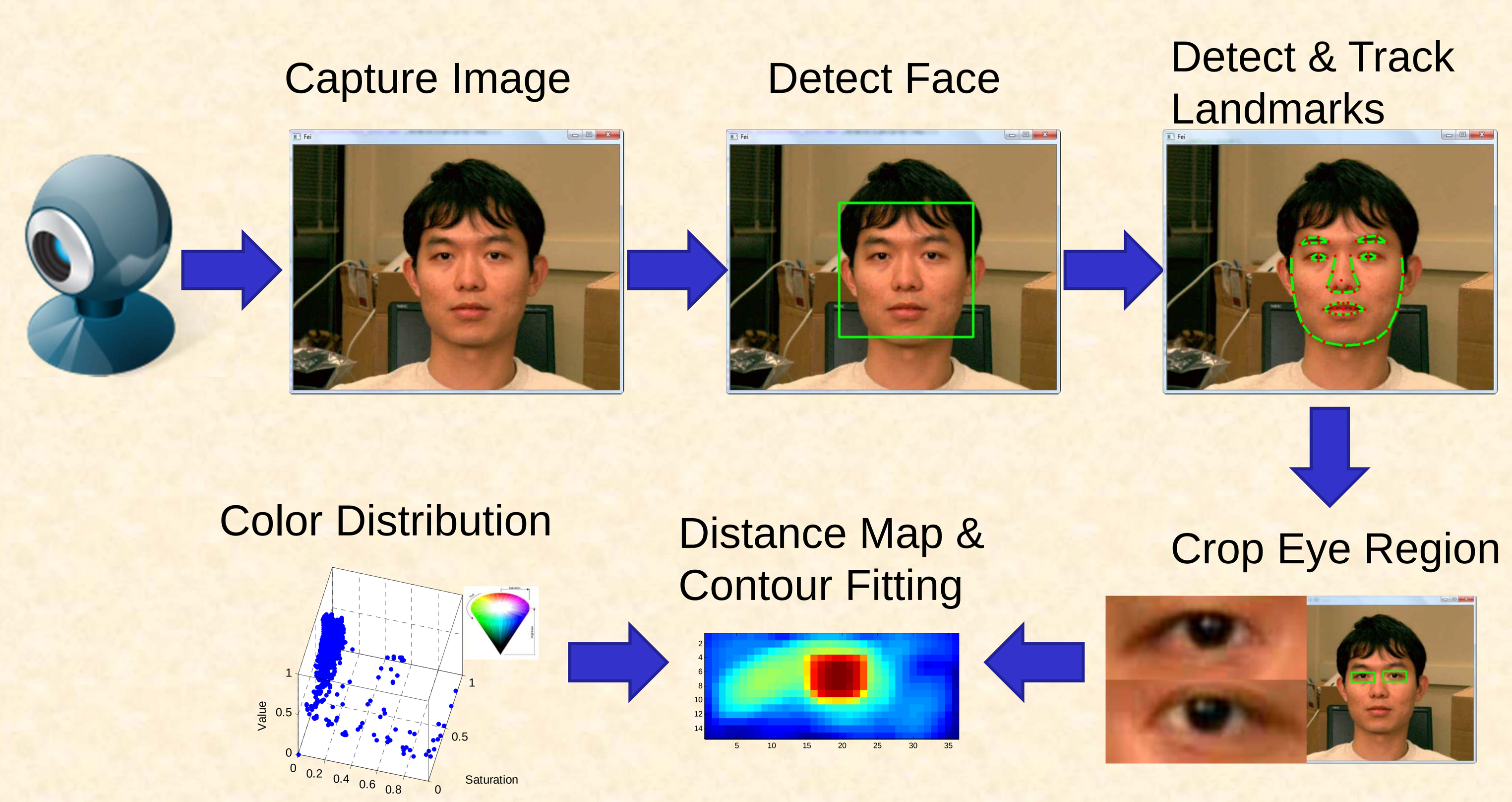


Fig 1. System flowchart

SUPPORT: NSBRI through NASA NCC 9-58

Find Color Distribution

We perform an expectation maximization algorithm to cluster the pixels in HSV color space.

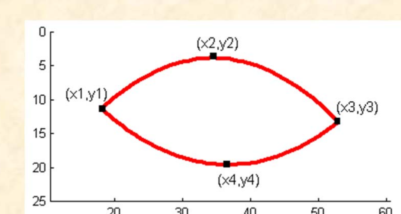
ALG: Find Skin Color Distribution

1. Crop eye region, convert to HSV color space.
2. Put all pixels in Set P.
3. Repeat
4. Compute Gaussian distribution (μ, σ) of all pixels in P.
5. For all pixels in eye region, compute the Mahalanobis distance to (μ, σ).
6. Take 50% pixels with smaller distances to μ and update P.
7. Until (μ, σ) converges.

Fit Eye Contour

We define the eye template as two parabolic sections. The parameters are then optimized to best fit the pixel-wise likelihood by using gradient descent method. Denote the parameters of the upper section as θ_1 and the parameters of the lower section as θ_2.

- The likelihood is



$$L(\theta|I) = (L(\theta_1|I) + L(\theta_2|I))$$
$$= \int_{x=x1}^{x2} \int_{y=y1(x)}^{y2(x)} s\big(I(x,y)\big)\,dy\,dx$$

- Compute θ_1 and θ_2 by fitting parabolic sections to pass the landmarks $(x_1, y_1) \dots (x_4, y_4)$
- Compute the derivatives of the likelihood L to the parameters θ_1 and θ_2.
- Compute the derivatives of L to $y_1 \dots y_4$.
- Update $y_1 \dots y_4$ by using gradient descent.
- Repeat the above steps until $y_1 \dots y_4$ converge.

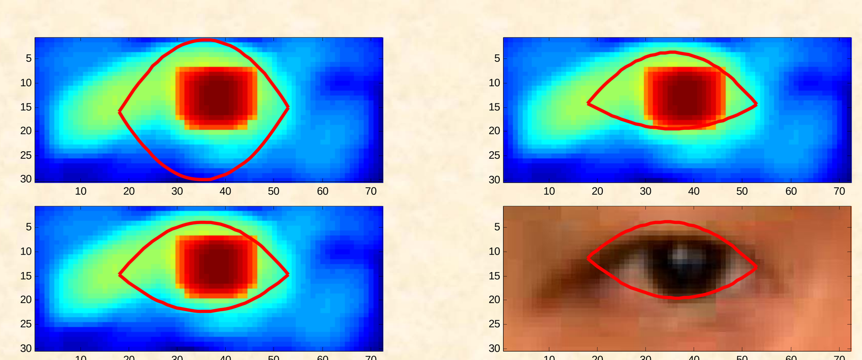


Fig 2. Eye contour fitting procedure

Experimental Results

We perform experiments both on the PERCLOS database provided by Dr. David F. Dinges and colleagues, and videos captured by a web camera.

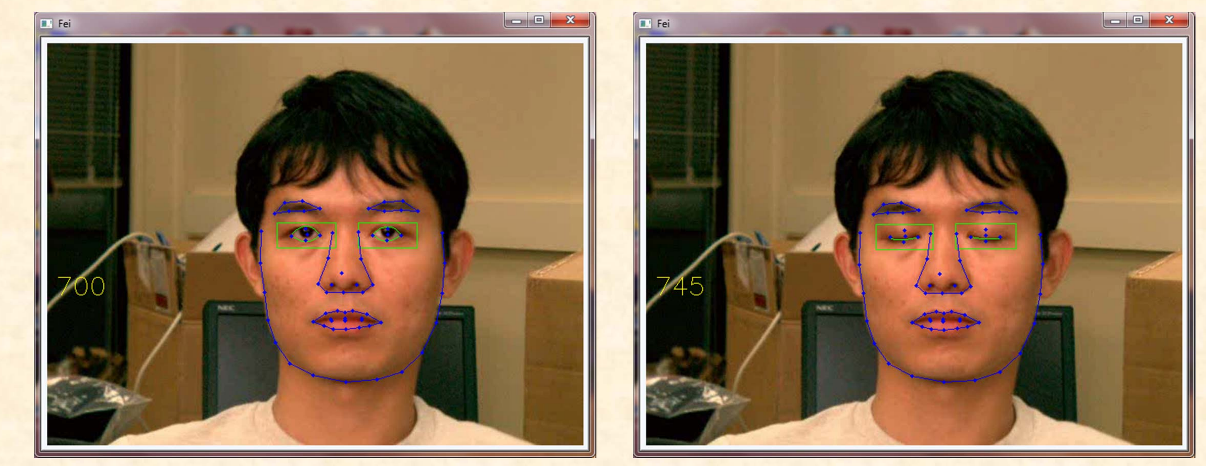


Fig 3. Landmark localization and eye contour fitting

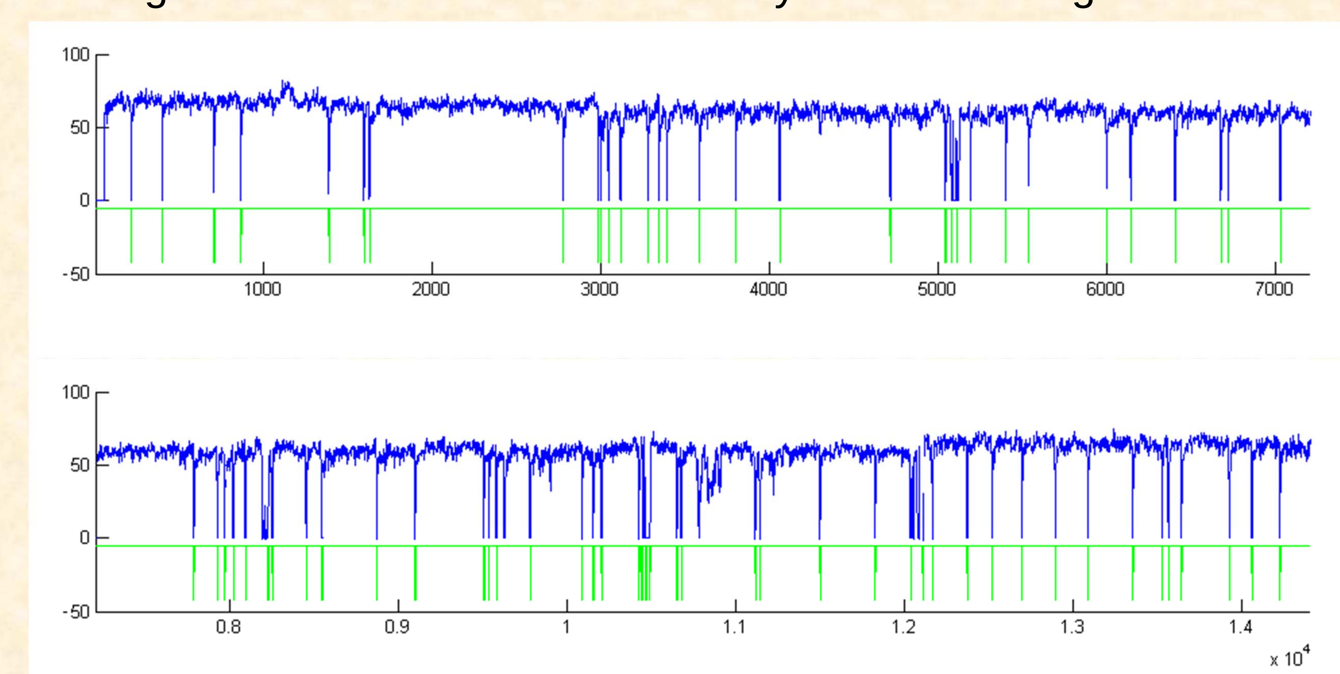


Fig 4. PERCLOS scores of a subject who stays clear

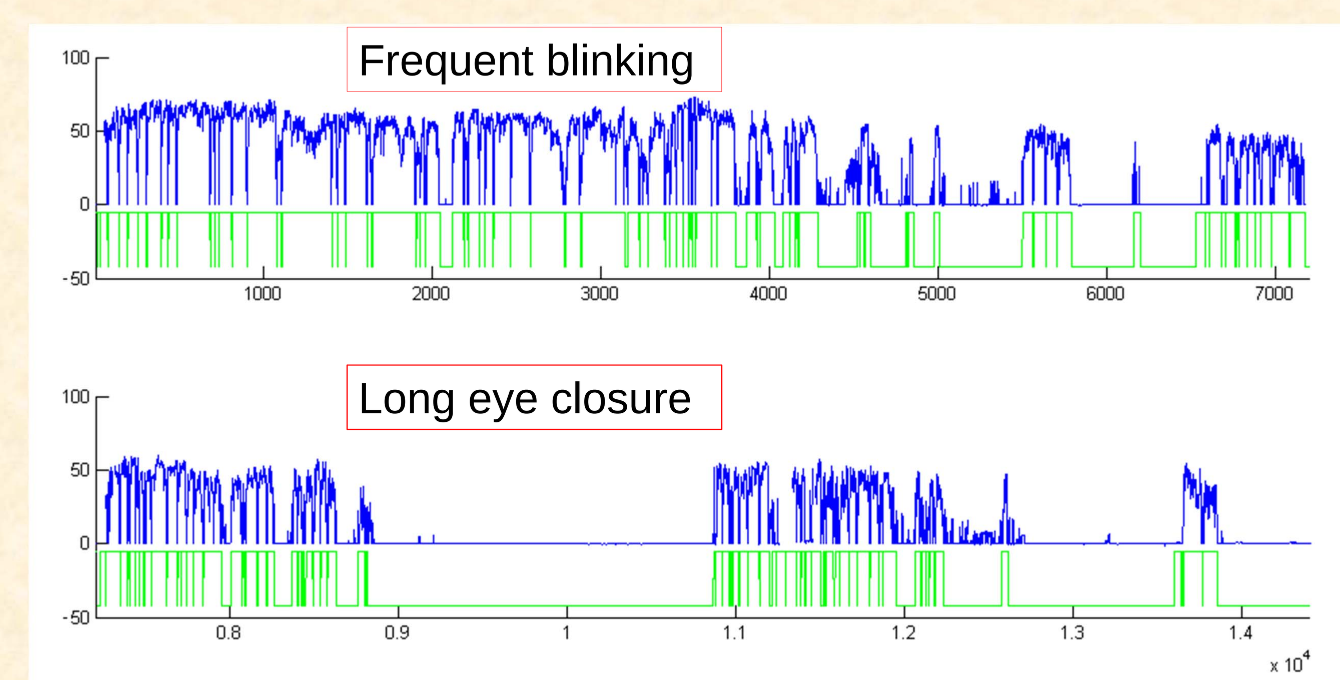


Fig 5. PERCLOS scores of a subject who is fatigue

References

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