Demo Abstract: Wireless Glasses for Non-contact Facial Expression Monitoring

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ABSTRACT

Facial expression monitoring is crucial in fields including mental health care, driver assistant systems, and advertising. However, existing systems typically rely on cameras that capture entire faces, or contact-based bio-signal sensors, which are neither comfortable nor portable. In this demonstration, we present a wireless glasses system for non-contact facial expression monitoring. The system is composed of an IR camera and an embedded processing unit mounted on a 3D-printed glasses frame, and a novel data processing pipeline running across the glasses platform and a computer. Our system performs high-accuracy and real-time facial expression detection with a running time of up to 9 hours. We will show the fully-functioning wearable system in this demonstration.

KEYWORDS

Wearable system, facial expression monitoring, glasses

1 INTRODUCTION

Facial expression monitoring is a very popular topic because of its high research and commercial values. It has a wide range of applications in fields including mental health care [7], driver assistant systems [6] and advertising [2].

Various methods of detecting human facial expressions have been proposed. They mainly fall into two categories: vision-based or bio-signals based. Vision-based methods detect facial expression with images of the whole face and have been extensively investigated in the past few years, with some promising results [5]. Nevertheless, these approaches require continuous capturing user's entire face with a camera looking from a distance, which is not portable and can lead to privacy concerns. On the other hand, wearable devices are becoming more and more popular, and provide in-situ sensing capabilities [9] [4]. However, existing research on facial expression sensing with wearable devices mostly uses Electromyography (EMG) signals [1]. These methods require constant contact between the electrodes and the skin to get reliable measurements, making long-term use uncomfortable.

To address these issues, we propose a wireless glasses system that can detect human facial expressions in a non-contact and privacy-preserved manner. It combines an image capturing and transmission unit mounted on a glasses frame, and a novel landmarks and optical flow based classifier running on a laptop computer to detect human facial expressions in real-time with high accuracy.

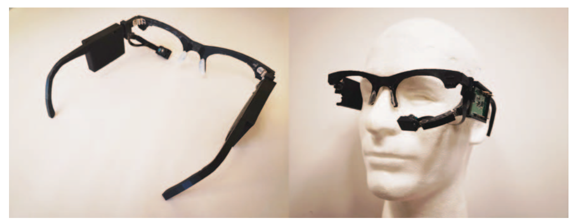

Figure 1: The wireless facial expression monitoring glasses.

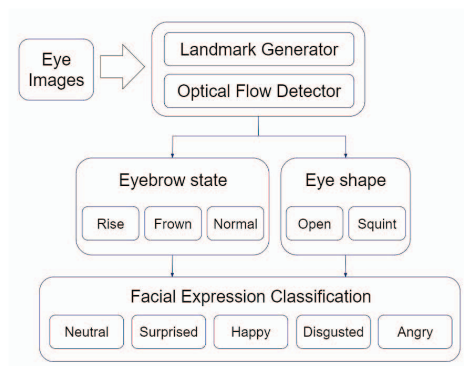

Figure 2: System diagram.

2 SYSTEM IMPLEMENTATION

The system consists of the embedded front-end glasses and the classifier running on the computer. The glasses capture images of the eye area, as shown in Figure 1, and the feature extraction module detects landmarks and optical flow motion vectors, as shown in Figure 3. Then the eye shapes and eyebrow movements features are combined to classify facial expressions.

2.1 Hardware Platform

The embedded front-end hardware consists of electronic components including an IR camera, two IR LEDs, and a wireless MCU, all mounted on a 3D-printed glasses frame. We choose an IR camera because it not only makes the images less affected by visible light but also enables our platform to perform pupillometry. The IR

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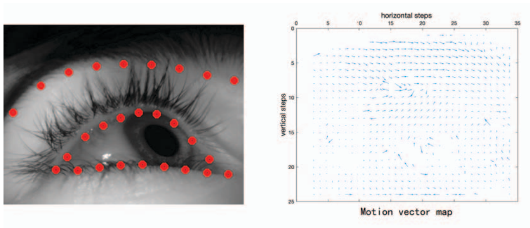

Figure 3: Left: example image of the eye with landmarks detected. Right: motion vector map of a frown.

Eyebrow/ Eye	Neutral Eyebrow	Frowning Eyebrow	Raised Eyebrow
Neutral Eye	Neutral/ Sad	Angry/ Fearful	Surprised
Squinted Eye	Happy	Disgusted	N.A.

Figure 4: Classification logic.

camera captures the images of the eye area illuminated by the IR LEDs and sends the JPEG compressed images to the wireless MCU. The JPEG compression is critical in reducing the size of the data, given the limited computing power and transmission capability of the wireless MCU. An HTTP server running on the wireless MCU streams the image frames upon request.

2.2 Eye Size Estimation

We use the area of the eye-opening to determine if the eye is squinting or non-squinting. To accomplish this, we need to detect the location and the outline of the eyelids. The area encompassed by the outline of the eyelids is directly correlated to the state of the eye: if the area is large then the eye is wide open, and if the area is small then the person is squinting. We train a convolutional neural network as a landmark generator to generate discrete points that outline the eyelids and the eyebrow. We fit two polynomial curves each to the landmarks of the upper and lower eyelids and calculate the area between them. We determine the detecting threshold using the largest and smallest areas of the eye. Eye areas above the threshold are considered non-squinting, and eye areas below it are considered squinting.

2.3 Eyebrow Movement Tracking

Besides checking for squinting eyes, tracking the movements of the eyebrow helps provide information about when the subject frowns or raises the eyebrows. Optical flow is the distribution of apparent velocities of movement patterns in an image [3]. It can provide us the movement pattern of the eyebrow. To achieve real-time performance, we adapt the PWC-Net proposed in [8] to calculate the optical flow between frames. We calculate the eyebrow movements as the mean of the motion vectors close to the eyebrow located by the landmarks.

2.4 Facial Expression Classification

We observe that the eye shapes and eyebrow movements are the two features that are more consistent among people of different races, genders, and cultural backgrounds, and show greater variation among different facial expressions. For instance, when a person shows a surprised face, the eyebrows raise and the eyes become wide open; when a person shows a disgusted face, the eyebrows are brought together and the eyes are squinted. Based on observations and empirical analysis, we use the logic shown in Figure 4 to classify states with different eye sizes and eyebrow movements into five categories.

3 DEMONSTRATION DESCRIPTION

In this demonstration, we will bring a pair of wireless facial expression monitoring glasses. A laptop running the classification pipeline will be provided and the audience will be invited to wear our device and make different facial expressions to evaluate the performance of our system. We will visualize the eye sizes and eyebrow movements and display real-time facial expression detection results on the laptop screen.

4 ACKNOWLEDGEMENTS

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