Towards Long-Term Large-Scale Visual Health Monitoring Using Cyber Glasses

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***Abstract*—More than 30% of the world population have vision defects, for some of which causes are still unclear. Visual health monitoring for detection, prevention, and treatment is possible but still very limited due to limited access to expensive specialized equipment and domain experts. Therefore, it is difficult to provide long-term visual health monitoring for a large population. In this paper, we present the design and evaluation of Cyber Glasses, low-cost computational glasses as a step toward long-term large-scale human visual health monitoring. At the core of Cyber Glasses are three key novel contributions: an integration of low-cost commercial off the shelf (COTS) components, an adaptive data collection mechanism taking into account tradeoffs between sensing accuracy, latency, memory, and energy, and a suit of energy efficient algorithms to reduce sensor data size and to extract meaningful human vision information to high-level applications. We conduct a number of experiments to verify the feasibility of Cyber Glasses to enable long-term large-scale human visual health monitoring.**

I. Introduction

Human vision is the primary sense that provides approximately 80% of the information received from the physical world as well as important information about individual health [1]. More than 30% of the world population have vision defects such as myopia [2], which is an eye disease causing nearsighted vision and is associated with increased risk of premature cataracts, glaucoma, retinal detachment and muscular degeneration [2]. Human vision defects have great negative impacts on human health, productivity, and social welfare. For example, myopia is an increasing trend in Singapore with 80% of the population affected, causing a shortage in army recruitment [3].

Visual health monitoring for detection, prevention, and treatment is possible but still very limited due to limited access to expensive specialized equipment and domain experts. For example, a patient has to make an appointment, pay fees, and go to a clinic to get eyes checked by a doctor. Thus, it is difficult to provide visual health monitoring to a large population for an extended period of time. As a result, diagnostics are typically passive; people realize a problem only when they notice some symptoms (e.g., blurred images). In addition, due to the lack of human vision information collected from a large population for a long period of time, causes of and prevention for eye diseases like myopia are not well understood. Indeed, it is still controversial about roles of genetics, nutrition, environment, and vision activities like prolonged close work in causing myopia [4].

We believe that *long-term large-scale* human visual health monitoring is essential in improving human visual health. Long-term monitoring can allow us to detect early vital signs, to understand the progression of some vision problems, and to have timely preventive solutions. Large-scale monitoring can allow us to understand better causes of visual health problems across geographical regions, origins, and socioeconomic status. A visual health monitoring framework must be low-cost, ubiquitous, and unobtrusive. One way to achieve this goal is to instrument eyeglasses to collect various information about the human eyes. It is, however, challenging to provide sensing services on low-power embedded platforms with limited memory, energy, and computation.

In this paper, we design and evaluate Cyber Glasses, which have integrated sensing, computation, and communication capabilities to enable long-term large-scale human vision health monitoring. At the core of Cyber Glasses are three key novel contributions: an integration of low-cost commercial off the shelf (COTS) components, an adaptive data collection mechanism taking into account tradeoffs between sensing accuracy, latency, memory, and energy, and a suit of energy efficient algorithms to extract meaningful human vision information to high level applications. The total cost of the COTS components is less than \$200. We conduct a number of experiments to verify the feasibility of Cyber Glasses in enabling long-term large-scale human visual health monitoring.

The contributions of the paper are following.

- Design and evaluation of a low-cost Cyber Glasses with integrated sensing, communication, and computation for human visual health monitoring.
- Development of efficient sensor data compression and collection mechanisms that reduce the amount of data stored and transmitted, thus conserves memory, energy, and bandwidth to prolong the glasses lifetime.
- An analysis of tradeoffs for various parameters including sensing quality, delay, and energy consumption. Based on our analysis, it is possible to provide long-term large-scale human visual health monitoring using Cyber Glasses.

In the following sections, we present background in human vision and requirements for a visual health monitoring framework (Section II). Based on the requirements, we describe the design of our monitoring framework based on Cyber Glasses

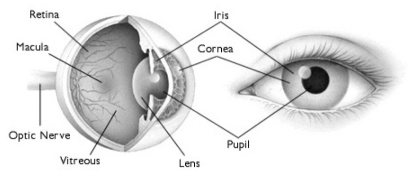


Fig. 1. Basic Eye Anatomy (Adopted from [5]).

with specific rationale about choices of sensors, networking technologies, as well as data processing and collection algorithms in Section III. We evaluate the feasibility of Cyber Glasses to enable long-term large-scale visual health monitoring in Section IV as well as our case study on extracting meaningful health-related information and classifying user activities based on blinks using Cyber Glasses in Section V. Finally, we conclude the paper in Section VI.

II. VISUAL HEALTH MONITORING REQUIREMENTS

The goal of this work is to enable human vision monitoring based on Cyber Glasses over a large population for an extended period of time. Based on recommendation from [4] and discussions with optometry researchers, we define a vision profile to be collected as a set of parameters encompassing viewing information and eye states. We briefly describe here main parameters as well as what they can contribute to understanding of visual health problems.

Viewing information includes:

- Viewing distance: Distance from eyes to the viewing object. Collecting viewing distance over time can provide a good understanding of how users use their eyes and can relate that information to certain diseases.
- Interrupt: Number of times users change their view in a period of time. This information is useful to detect unhealthy behavior such as staring at an object for a long time.
- Viewing angle: The angle of the eyesight and the surface of the viewing object. This information is useful to detect abnormality in eye behavior.
- Ambient light, temperature, and humidity: These are ambient conditions around the eyes. This information can help providing useful feedback to users to change the ambient conditions to keep their eyes healthy.

Eye states include (refer to Figure 1 for basic eye anatomy):

- Pupil position and size: Pupil position and size can provide useful information about the user health as well as emotion.
- Accommodation: Accommodation is the process by which the vertebrate eye changes optical power to maintain a clear image (focus) on an object as its distance varies. This information is useful in understanding causes and progression of vision defects such as myopia.
- Eye aperture size: The opening of the iris so that different amount of light can enter into the eye. This information is useful in understanding the eye reaction to different stimulus.
- Blink frequency: Blinking is a quick eye motion of closing and opening the eyelids. Blink frequency is the number of times a user blinks eyes in a period of time. This information is useful in understanding the user general health, emotion or activities.
- Eye squinting: A user squints eyes when the user looks with the eyes partly closed. This information is useful in understanding the user concentration.
- Strabismus: A condition in which eyes are not properly aligned with each other. This information is useful in detecting early sign of abnormality of the eyes.

TABLE I. SENSING REQUIREMENTS AND HEALTH CARE APPLICATIONS.

Sensing requirements	**Health care research/applications**
Viewing distance	Close work prevention
Interrupt	Close work prevention
Viewing angle	Abnormality detection
Ambient conditions	Dry eye prevention, adaptive environment
Blink frequency	Activity classification, detection of drowsiness
Eye squinting	Detection of drowsiness
Strabismus	Abnormality detection
Pupil position and size	Abnormality detection
Eye aperture size	Abnormality detection

Table I summarizes main sensing requirements and their health care applications. In addition, the monitoring framework must also be low-cost, ubiquitous, and unobtrusive to be practically deployed in a large population.

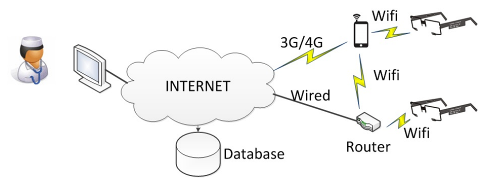
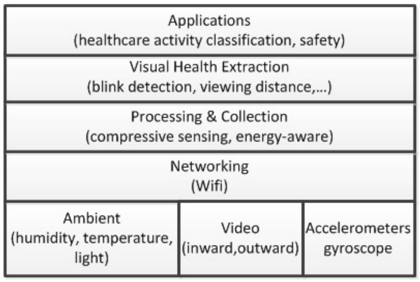


Fig. 2. Networking Options for Cyber Glasses.

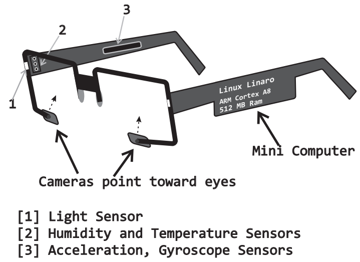
III. VISION MONITORING FRAMEWORK WITH CYBER GLASSES

We now present our framework using Cyber Glasses to enable vision monitoring with the above health related requirements as well as system requirements including low-cost, ubiquitous, and unobtrusive. Figure 2 shows the overall architecture of the framework. At a high level, Cyber Glasses collect vision profile from a user. The information is forwarded to a database or cloud-based repository over the Internet. Health care experts who have permissions to access the information can provide more insight feedback to the user as well as understand more about causes and progression of certain visual health diseases. The sharing and feedback of health information can utilize existing work in mobile health integration such as Open mHealth [6] and are not the focus of this paper. Instead, we focus on the design of Cyber Glasses as well as system support to smoothly integrate our vision health monitoring framework in Figure 2.

Figure 3(a), 3(b), and 3(c) show the platform overview, our design concept, and the actual prototype that we have developed respectively. The platform is organized into five main



(a) Platform Overview



(b) Cyber Glasses Concept

(c) Cyber Glasses Prototype

layers: *sensing, networking, processing and collection, visual health extraction, and application*. The sensing layer is responsible for collecting physical measurements that contain visual health information. The networking layer is responsible for providing connectivity to other devices (e.g., a smart phone) and to the Internet so that sensing data can be transferred to a common repository. The processing and collection layer is responsible for compressing data and deciding how data are reported (e.g., streaming video in real-time or storing the video and forwarding them later). The visual health information extraction layer is a suit of algorithms that extract various vision parameters described in Section II from the collected data. Finally, the application layer contains a set of applications or enabled research in healthcare.

Cyber Glasses are built from commercial off the shelf (COTS) components. The glasses frame is taken from regular eyeglasses. The frame is strong enough to carry other components including embedded processing unit, sensors, cameras, and batteries. The camera is placed in the lower front of the eye. The camera is placed close to lower eyelid to be able to capture images of the whole eye. Other sensors are placed at various locations on the frame. The embedded processing unit is embedded on the glasses in the left temple. Battery is embedded in the right temple.

We use an embedded processing unit (MK802), which contains an ARM Cortex A8 processor with 512MB RAM. It can support Android Cream Sandwich and Linux Linaro operating systems. Although Android is more energy efficient than Lunux Linaro, we use Linux Linaro for the first prototype due to its better hardware compatibility. We use Innergie PocketCell battery, which has a capacity of 3000 mAh at 5V and can power the Cyber Glasses through USB 2.0 connection. We use a Sony PlayStation Eye Camera, which satisfies video quality, frame rate, and hardware compatibility. Finally, we use various sensors from Phidgets for ambient, acceleration, and gyroscope sensing. The following sections will describe each layer in detail.

A. Sensing

At the sensing layer, various sensors are selected based on the vision monitoring requirements described in Section II. The sensors are organized into three categories; ambient sensors (e.g., light, humidity, and temperature), video, and context sensors (e.g., accelerometer, and gyroscope).

For all sensors and cameras, they should have low cost, small size, high accuracy, and low energy consumption. For ambient sensors such as humidity, temperature, and light sensors as well as context sensors such as accelerometer and gyroscope, we use sensors from Phidgets [7]. These sensors are low-cost and plug-and-play. Thus, it is relatively easy to add new sensors as well as place sensors at different locations on the frame to study their impacts on sensing. There is an interface board that connects to these sensors to the MK802 minicomputer through USB. We attach sensors around the eye region to record ambient light, humidity and temperature around both eyes.

For cameras, both outward and inward facing cameras are needed. Integrating outward facing cameras is straightforward. Integrating inward facing cameras is challenging because there are some tradeoffs that we need to consider in choosing a camera. First, a camera should capture qualifying videos in terms of image quality (320x480) and frame rate (30 fps). These are two essential requirements enabling eye-monitoring applications. Second, because of close distance from the camera to the eye, the camera needs to have large enough field of view to capture the whole eye and also needs to have a correct focus. Third, cameras should be small enough to easily attach to the glasses without making user uncomfortable while wearing the glasses. Moreover, cameras attached in front of the eye should not block the user's view. In the very first prototype, we decide to use a Red-Green-Blue (RGB) Sony PlayStation Eye Camera, which satisfy video quality, frame rate and hardware compatibility.

A limitation of our current design using RGB cameras is that the cameras must be pointing toward the eyes to capture images of the eyes. Thus, they will not be completely unobtrusive. A possible alternative option is to use infrared cameras mounted on the side of the frame to capture infrared images reflected from transparent IR-mirror on the glasses lenses themselves. This option is promising and has actually been applied in Tobii glasses [8]. However, extra components including IR emitter, IR reflector, and special glasses lenses are required. Our design does not require users to wear lenses. In addition, extra energy will be needed for the IR-emitter to emit IR light to the eyes. Finally, IR images are in grey scale, which may not contain certain information of the eyes compared to colored images (e.g., color of red eyes). We use the Sony PlayStation Eye Camera mainly for compatibility reasons. With a holistic design in production, we believe that much smaller wide-angle cameras can be integrated without viewing obstruction.

GPS and compass can be useful to provide sensing data context. For example, they can provide extra information about where the user is and which direction the user is looking

TABLE II. SENSORS FOR CYBER GLASSES.

Sensors	Requirements
Outward cameras	Viewing distance, interrupt, viewing angle
Inward cameras	Blinking, squinting, Strabismus, Accommodation and aperture size
Light, Humidity Temperature	Ambient conditions
Accelerometer	View interrupt
Gyroscope	Viewing angle

at. They, however, are more useful for interaction with the physical world than for health monitoring purposes. Hence, we do not include them in our prototype. Several other health parameters such as pulse, skin temperature, brainwave (EEG), and heartbeat (ECG) signals are also very useful for health monitoring. However, they often require semi-invasive sensors (e.g., sensors attached to skin). Hence, we decide not to include these sensors in our design.

Table II shows the mapping between the sensors and the requirements that the sensor data can potentially provide.

B. Networking

There are several networking technologies including 3G/4G, Wifi, Bluetooth, and Zigbee for Cyber Glasses to connect to a network to transfer sensor data. Each technology has its own advantages and disadvantages. Given the requirements on low-cost and high data rate, Wifi and Bluetooth are the two most suitable choices for Cyber Glasses. We chose Wifi for our prototype for several reasons. First, it is already available on the MK802 platform. Second, it is much easier to integrate with existing services (e.g., cloud storage) on the Internet. Finally, it can leverage existing Wifi infrastructure in office and residential buildings. It does not require a third device to act as a gateway to the Internet like Bluetooth. Cyber Glasses still can connect to a Wifi enabled device (e.g., smart phone) if it is necessary. Although, Wifi consumes more energy compared to Bluetooth, our initial prototype shows that Cyber Glasses with Wifi can have a reasonable lifetime. Our evaluation of energy consumption is described in detail in Section IV.

C. Processing and Data Collection

Sensor data processing and collection consume a significant amount of energy and are essential to prolonging the Cyber Glasses lifetime. Ideally, the amount of data being collected and transmitted should be minimized. However, video intrinsically has large size. Thus, it is important to efficiently compress video as well as other sensor data for processing and transmission. In the following subsections, we present several techniques to reduce the amount of sensor data for transmission, storage (Section III-C1), and processing (Section III-C2). We also present an adaptive data collection mechanism (Section III-C3) to extend the Cyber Glasses lifetime.

1) Content Driven Video Compression: One problem with long-term monitoring with cameras is the large storage requirement for video data. Currently we use a camera can capture video at a resolution of 320x240 at 30 fps. However, in the real integration, it can record video at about 20 fps. The amount of memory storage required to store video at the above resolution in MPEG-4 format, a popular video format for low resolution video, for 30 minutes, 1 hour, and 2 hours are 127 MB, 308 MB, and 807 MB respectively. With a large capacity secure digital (SD) card (e.g., 32GB micro SD card), we can capture and store video for more than a day and upload the video to a server when the glasses are connected to the Internet. However, the large amount of video data itself requires significant processing and networking resources. Therefore, it is important to reduce the amount of video data.

One approach is to reduce the resolution of video frame (e.g., to 60x80). The reduction of frame size will lose certain information in the video. Moreover, for wearable devices, video resizing is a computationally heavy task that requires significant amount of energy. Regular COTS cameras often have certain resolution that allows highest frame rate (usually 30 fps for current 2.0 USB interface). Further reducing the video resolution will affect the recording frame rate, which is critical in some applications such as blinking detection.

In this paper, we propose a content driven approach to optimize the storage for Cyber Glasses. The key observation is that for cameras pointing towards the eyes, the recorded images have similar content structure (e.g., the eye shape). Therefore, we apply eigen-eye [9], a set of vectors containing main features in images of eyes. From a dataset of eyes, we extract eigen-eye using Principal Component Analysis (PCA), which convert a set of images of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components [10]. PCA is applied to capture the variance in the given dataset. In [11], PCA was applied to extract eigenface for human face recognition. Note that in Cyber Glasses, inward cameras are used to capture images of the user's eyes. The most variances of the eye images are the states of the eye of a user (e.g., closing, opening, gazing) and between users. Instead of storing the captured video, for each video frame, we just need to store the first n coefficients after projecting that video frame onto an extracted subspace of basis images. The subspace constructed by first n basis images conveys the most variance of the given dataset. So, by using those first n coefficients, we can reconstruct the original frames with negligible error. Therefore, applying PCA to the dataset of eye images to extract eigen-eye reduces the amount of data storage.

To apply the eigen-eye approach to Cyber Glasses, we prepare a collection of eye images and apply PCA to extract basis images. The subset of n basis images, which contain the most variance of the dataset, is stored in the server and synchronized with Cyber Glasses via cloud synchronization technique (Figure 3). Cloud synchronization helps quickly update the trained results to the Cyber Glasses. These enable continuous monitoring over a large scale. One slightly different approach is to store and extract set of basic vectors for each single person. However we try it and see that it did not increase the contribution of first n basis vectors significantly compared to a generic dataset of multiple users.

2) Compressive Sensing: We consider applying compressive sensing (CS) [12] techniques to reduce the amount of sensor data. In compressive sensing, a high dimensional *sparse* signal can be reconstructed exactly from only a small number of measurements. Consider a signal f represented in the standard basis as a vector of length n, where $f \in R^n$. f can also be represented in another bases such as Fast Fourier Transform (FFT) using a coefficient vector $\hat{f} \in R^n$. The basis

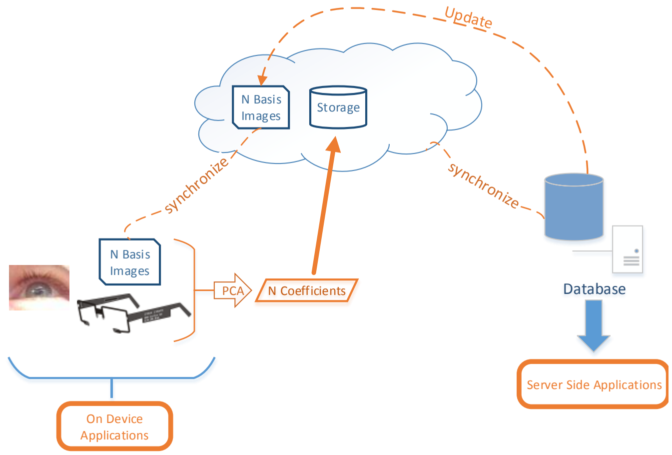


Fig. 3. Content Driven Video Compression: Video frames are projected onto a subspace of basis images to get n coefficients. Only these n coefficients are stored in a database. Extracting and synchronizing n basis images are driven by specific application.

function can be characterized by an invertible matrix $\Psi \in R^{nn}$ and the relation between f and $\hat{f}$ can be stated as:

$$f = \Psi \hat{f} \text{ and } \hat{f} = \Psi^{1} f$$

The key idea is that if a signal f is sparse (i.e., it can be expressed in some domain as $\hat{f}$ in a few linear combinations of basis functions), then we can reconstruct the signal from a few *measurements*. One way to obtain these measurements is to project the signal f using a random matrix.

Let m be the number of random measurements can be obtained as a vector $h \in R^m$ by projecting f to a projection matrix P of m by n random entries, i.e., $h = Pf$. Projection can be obtained by special hardware [13] or by sampling the signal first then compute the projection.

One key theoretical result is that if $m \geq c \times |k| \times \log n$ where c is a constant, k is the number of non-zero coefficients of f in the domain that f is sparse, then solving the optimization problem

$$\sum_{t=0}^{t=n-1} |g(t)| \text{ such that } \hat{g(\omega)} = \hat{f(\omega)} \text{ for all } \omega \in \Omega$$

will give f exactly with overwhelming probability. There may be measurement noise in an application, another theoretical result states that the reconstruction error is bounded and proportional to the noise level in most cases [14].

Compressive sensing is useful when (i) measurements are expensive to obtain (e.g., magnetic resonance imaging [15]) or (ii) computation is expensive in the original signal domain (e.g., video background subtraction [16], [17]). For Cyber Glasses, compressive sensing can be helpful to reduce the captured video to a small number of measurements to calculate viewing distance or blinking rate efficiently. To apply CS in Cyber Glasses, we construct a random Bernoulli projection matrix with value +1/-1. We project each video frame to the projection matrix to get a vector of compressive measurements. Then, we apply PCA to extract the structure of dataset of the compressive measurements. We will show that compressive sensing works well for close-eye detection, an important step in eye-blink detection in Section IV-B4.

3) Energy Aware Adaptive Data Collection: Data collection consumes a significant amount of energy and directly affects the Cyber Glasses lifetime. Key parameters in the data collection are the amount of computation to be done at the device itself, the amount of data being transmitted, and the time Cyber Glasses has to keep the network module (e.g., radio) on for transmission. We consider three main data collection mechanisms: in-device processing, stored and forward, and real-time streaming. Their description as well as qualitative tradeoffs in terms of energy, latency, and memory are described in Table III.

We present detail quantitative evaluation of these tradeoffs in Section IV-B. The key challenge is to adaptively choose a data collection mechanism based on application requirements (e.g., real-time monitoring) and the energy budget of the Cyber Glasses. We propose an energy aware adaptive data collection algorithm that takes into account the application minimum sampling requirements, minimum lifetime requirement, and latency to adjust the Cyber Glasses operation to maximize its lifetime. At the core of the algorithm is a linear optimization problem that maximize the Cyber Glasses lifetime while satisfying the minimum sampling requirement, minimum lifetime, and latency subject to the device energy and storage budget as well as network availability.

D. Applications

This layer contains a number of applications based on Cyber Glasses. The applications can be detecting drowsiness, detecting abnormal or vital signs, or classifying user emotional level. Collectively, data collected from a large population can enable understanding of causes and progression of some visual health diseases. In this paper, we will present our results in evaluating a blinking detection algorithm that we developed specifically for low-power embedded devices like Cyber Glasses in Section V.

IV. Evaluation

A. Goal and Metrics

There can be a number of aspects to be evaluated for Cyber Glasses. In this paper, we focus on evaluating the feasibility of using Cyber Glasses for (i) *long-term* and (ii) *large-scale* human visual health monitoring. In terms of *long-term*, we analyze the energy consumption in various configurations to see if feasible to provide continuous monitoring for the whole day. Our assumption is that, the Cyber Glasses can be recharged daily just like other personal computing devices such as phones and laptops. In terms of *large-scale*, we develop a blink-based activity classification application and conduct real experiments with a small number of people. We evaluate if it is feasible to extract high-level information from Cyber Glasses across different people. We understand that a real clinical trial with a large number of participants would reveal more insights about this aspect. However, it will be our future work.

B. Evaluation Results

In this section, we present our evaluation results in terms of energy consumption for different device configurations, latency and energy consumption tradeoff, content driven data compression, and compressive sensing.

TABLE III. DATA COLLECTION MECHANISMS FOR CYBER GLASSES.

Collection Mechanism	Description	Energy, latency, and memory tradeoff
In-device processing	Process all measurements in Cyber Glasses, store the results and only report data when networking is available	Cyber Glasses cannot process data fast enough. Results are delayed.
Stored and forward	Measurements are stored in Cyber Glasses and periodically or opportunistically reported to database	Require enough storage for data, delay varies depending on the reporting period.
Real-time streaming	Measurements are reported as soon as they are captured.	Cyber Glasses must be connected to a network at all time.

TABLE IV. CONFIGURATIONS.

Notation	Configuration
[1]	MK802
[2]	MK802, sensors
[3]	MK802, sensors, collecting data
[4]	MK802, camera
[5]	MK802, sensors, camera
[6]	MK802, sensors, camera, running blink detection algorithm
[7]	MK802, sensors, camera, collecting data, running blink detection algorithm

TABLE V. STORE AND FORWARD SETTINGS.

[Streaming]	streaming camera
[1m]	capture and store video of 1 min, keep synchronizing with cloud
[5m]	capture and store video of 5 min, Wifi is only on for synchronizing
[30m]	capture and store video of 30 min, Wifi is only on for synchronizing
[4h (1)]	capture and store video of 4 hours, Wifi is only on for synchronizing
[4h (2)]	capture and store video of 4 min, Wifi on for synchronizing only after having finished capturing

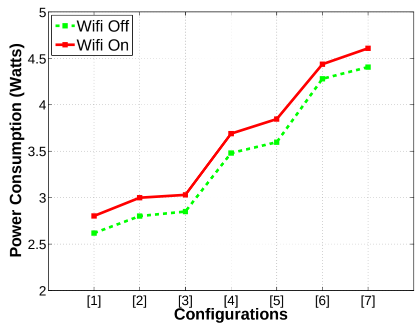


Fig. 4. Energy Consumption : The energy consumption ranges from 3 Watts to 4.5 Watts with a significant jump when the camera is active in configuration [4]. With a 3000 mAh $\times$ 5V battery, Cyber Glasses can run continuously from 4 to 5 hours.

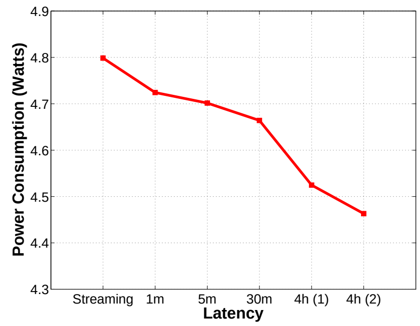


Fig. 5. Latency and Energy Consumption: As the delay duration increases, the energy consumption decreases. The tradeoff here is the increasing amount of memory for storing the captured video.

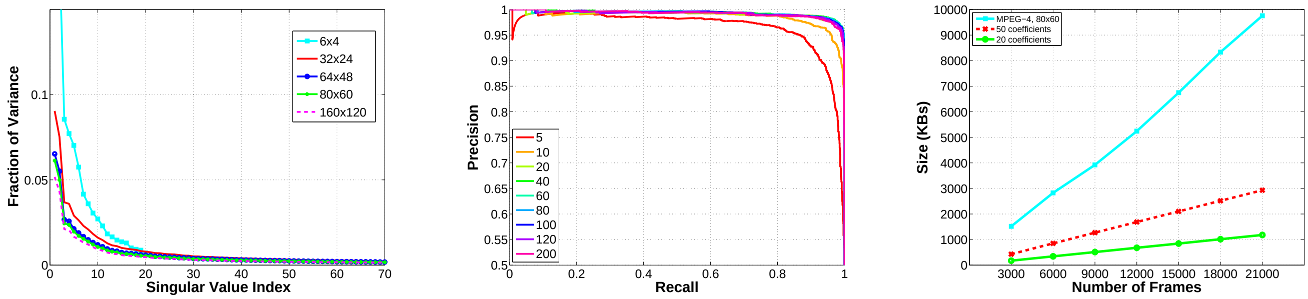
1) General Energy Consumption: We measure energy consumption for Cyber Glasses with different configurations described in Table IV.

Figure 4 shows the power consumption of Cyber Glasses in the above configurations with and without Wifi on. As expected, configurations with Wifi on always consume more energy than configurations with Wifi off. The energy consumption ranges from 3 Watts to 4.5 Watts with a significant jump when the camera is active in configuration [4]. With a 3000 mAh $\times$ 5V battery, Cyber Glasses can run continuously from 4 to 5 hours. With two batteries, Cyber Glasses can provide continuous monitoring for the whole day. With a more careful integration and optimization and increasing efficient energy storage technologies, Cyber Glasses can enable monitoring for days before being recharged.

2) Latency and Energy Tradeoff: Table V shows different settings for the store and forward data collection mechanism. We only analyze tradeoffs between latency and energy consumption for video because of its significant amount of data.

Figure 5 shows the energy consumption for the above settings. Streaming video consumes the most amount of energy. Other approaches capture video in blocks of 1, 5, 30, and 4 hours with wireless turned off and then only turned on at the end of each block to upload the video to a cloud storage. As the block duration increases, the energy consumption decreases. Another tradeoff here is the increasing amount of memory for storing the captured video. The energy saving comes from keeping the Wifi networking support off as much as possible. Hence, an optimal approach for data collecting is the delay reporting data as late as possible without violating the minimum latency requirement of the application.

3) Data Driven Video Compression: One of the possibility to reduce amount of storage is to further down sample video size and save in a different format other than the regular video codec MPEG-4. We down sample eye images to very small size and then reconstruct them back to the original size. We use bicubic interpolation as the resizing method. We select the same number of principle component coefficients as the number of pixels of the resized images. For example, for images of size 80x60, we down sample them to size 8x6, and also extract the first 48 PCA coefficients; for image of size 160x120, we down sample them to size 16x12, and also extract the first 192 PCA coefficients. We then reconstruct the resized images to the original size 80x60 and 160x120 respectively. We calculate average peak signal-to-noise ratio (PSNR) of pairs of original image and reconstructed images for both methods. The higher the PSNR is, the better the reconstruction is. Using PCA coefficients, the reconstructed images have the average PSNR of 29.5 and 32.5 compared to 25.5 and 29 using image



(a) Singular Value and Variance: small number of first n singular values, corresponding to first n basis images, captures the major variance of the training set of eye images.

(b) Close Eye Detection with Different Number of Basis of Image Size 80x60: using 20 basis image is enough to attain high accuracy for close-eye detection.

(c) Storage Size of Stored Video vs Stored Coefficients of Principle Components (PC): storing certain amount coefficients number of PC reduces significantly amount of storage.

resizing for 80x60 and 160x120 resolution respectively.

As shown Figure 6(a), the first 50 singular values correspond to first 50 basis images captures the major structure of the dataset. Figure 6 shows the original 120x160 images and the reconstructed images using 50 coefficients. Figure 6(b) shows the result of applying PCA to get coefficients and using those coefficients for detecting close eyes, a step in detecting eye-blinks. We achieve both precision and recall of more than 95%.

Figure 6(c) shows the amount of storage for both methods. Compared to the smallest video resolution we can capture at 80x60, the amount of data storage in our method is several times smaller.

4) Compressive Sensing: To apply Compressive Sensing for Cyber Glasses, we construct a random Bernoulli projection matrix with value +1/-1. We project each video frame to projection matrix to get a vector of compressed measurements. We then apply PCA to extract the structure of dataset of compressed measurements. The results are reported in Figure 7(a) with different compressing sizes. With a few compressive measurements, 96 coefficients compared to 80x60 images, the measurements still preserve the variance information of the original dataset.

We also test the same close-eye detection method using compressive measurements and show the results in Figure 7(b). We still can achieve a comparable performance (95% precision and 90% recall) in detecting close eyes. Thus, compressive measurements can potentially in many other applications such as inferring viewing distance from images.

V. Use Case: Blink-based Activity Classification

Further exploring capability of the Cyber Glasses, we conduct a real experiment using Cyber Glasses with an eye blink detection algorithm to capture blink patterns of different human activities (e.g., reading books or watching movies). We have developed a robust eye blink detection method for low-power embedded devices like Cyber Glasses. Since the detail development of the blink detection algorithm is not the focus on this paper, we do not describe our algorithm here.

Three users wear Cyber Glasses while reading books and watching video clips for ten minutes. We use Cyber Glasses to capture Spontaneous Eyeblink Rate (SEBR) and Inter-eyeblink Interval (IEBI), which are assessment method mentioned in [18]. Results are presented in Table VI and Figure 7(c). We can see a clear difference between the blinking rates for reading books and watching a movie. These very initial results can enable a deeper eye behavior study for visual health care experts.

TABLE VI. SEBR in activities.

Activity	user 1	user 2	user 3
Reading book	25.2	4.8	11.4
Watching video clips	21.6	9.8	19.0

The main purpose of the experiment is to show the practical use of the Cyber Glasses. Different from other eye-learning experiments [18], [19] conducted in lab environments, in short time and with a small scale, Cyber Glasses enable conducting experiments in different conditions, for longer time, and at larger scale. For example, Cyber Glasses can be used for group of students studying in the classroom with different light conditions to learn impacts of ambient lighting on students' concentration. Another example is to discover relationship of eye disease such as red-eye disease in different daily life scenarios.

VI. Conclusion

We design, develop, and evaluate low-cost Cyber Glasses, which have integrated sensing, communication, and computation to enable *long-term large-scale* human visual health monitoring. Cyber Glasses mainly use COST components. Cyber Glasses sensors and networking technologies are carefully considered based on the requirements for visual health monitoring as well as the limitation of embedded devices. We also propose and evaluate a suit of algorithms in Cyber Glasses to reduce the amount data being collected and transmitted in order to conserve energy to prolong the glasses lifetime. Results from real experiments show that Cyber Glasses can enable long-term large-scale visual health monitoring. Our example application shows that using Cyber Glasses, user activities can be correctly classified based on eye blinks.

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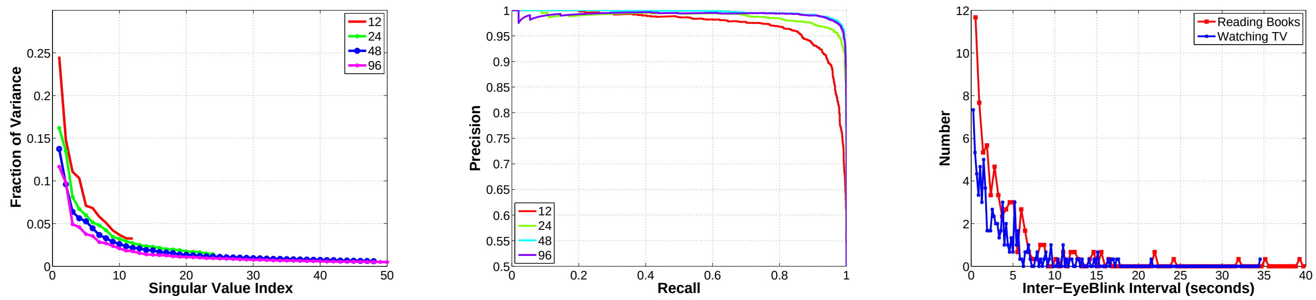
Fig. 6. PCA Reconstruction Using 50 Basis Images of Size 160x120: Original Images (above) and Reconstructed Images (below)



(a) Singular Value and Variance Fraction of Compressed Signal Using Compressive Sensing: compressive sensing preserve well variance of the training set.

(b) Close Eye Detection Using Different Compessive Sensing Ratio: applying compressive sensing technique can still keep high accuracy of close-eye detection.

(c) Inter-Eyeblink Interval in Different Activities: Cyber Glasses helps record and analyze eye-monitoring parameters in different activities and environments.

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