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Enhanced head-mounted eye tracking data analysis using super-resolution

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Abstract

This paper proposes a novel framework for enhancing head-mounted eye tracking data analysis by utilizing state-of-art computer vision techniques. Recently, the development of mobile eye tracking sensors allowed researchers to explore more comprehensive eye movements in an unobtrusive environment. It opened a door that stationary eye tracking devices could never approach. Literature demonstrates applications of mobile eye tracking technology to fields such as psychology, education and learning, usability, marketing, and medical diagnostics. The eye tracking research community is interested in analyzing the details of what and where a person is looking at using large-scale head-mounted eye tracking data. We formulated this problem to be eye tracking video processing, which can be resolved by locating at region-of-interests (ROI) based on fixation location, cropping and zooming in the ROI and enhancing the partial image by super-resolution image transformation. Experimental results and evaluation using image quality measurements show the effectiveness, efficiency, and robustness of the proposed prototype system. Furthermore, we discuss and demonstrate potential real-time applications using the proposed framework with emphasis on using an Augmented Reality (AR) headset with eye tracking capabilities.

1. Introduction

Rapid development of easily accessible eye tracking technology enables comprehensive exploration of eye movement behaviors. Commercially available eye tackers can be categorized into stationary remote eye trackers and head-mounted mobile eye trackers. The stationary eye trackers require research participants to sit relatively motionlessly in front of computers in order to capture stable eye movements' pictures by infrared cameras. Among others, they are used in human computer interaction experiments, reading and learning research [1, 2].

Recently, head-mounted eye trackers were developed for researchers to monitor and capture eye movements' and field-of-vision (FoV) information without restricting movements. They open a door to investigating research questions that remote eye tracking could never ever approach. In other words, participants are no longer forced to sit still facing a machine all the time to complete designed tasks. Instead, they can move around and interact with the real-world surroundings while their eye movements are captured.

The literature demonstrates that mobile eye tracking technology has been used widely in fields such as psychology, education and learning, usability, marketing, and medical diagnostics. Mobile eye tracking glasses have a frontal scene camera to capture the field of front view and multiple infrared cameras to illuminate and track pupil movements. A short calibration process, training and forming a mathematical equation allows the system to determine "where" someone was looking. Popular commercially available mobile eye trackers that are widely used by researchers are: SMI, pupil labs and Tobii [3].

Head-mounted eye tracking sensors provide two main benefits: it makes a device aware of what the user is interested in at any given point of time; and it provides an additional way to understand and interact with the interesting content. The eye tracking research community is interested in analyzing the details of what and where a person is looking at in large-scale head-mounted eye tracking data. In order to retrieve the fine details of the captured eye tracking video data and further analyzing it, researchers need the partial image, region-of-interests (ROI), to be as clear as possible.

Existing technical challenges inherent to mobile eye tracking research are: 1) Locating the area of interest people are fixating at while wearing head-mounted eye tackers (that is identifying the object within a recorded scene video); 2) generating a high-resolution output image from a low-resolution input in order to display the ROI as clear as possible; 3) reducing unpredictable background noise and illumination variations introduced from outdoor head-mounted eye tracking recordings. To the best of our knowledge, no work has been reported to comprehensively solve the head-mounted eye tracking data analyzing challenges mentioned above. This work, for the first time, proposes a novel framework for enhancing offline head-mounted eye tracking data analysis for presenting all the possible details within a ROI by utilizing state-of-art computer vision techniques. We formulated this to be an eye tracking video data processing problem, which can be resolved by locating, cropping and zooming in the area around fixation location and enhancing the ROI using deep-learning based super-resolution image transformation.

This paper thrusts to present a novel software solution for tackling the challenges mentioned above and hence replicating all the details with in ROI in offline head-mounted eye tracking data analysis. Hence researchers will be able to have a better view of what the participants' eyes were capturing. In addition, we demonstrate AR applications adopting our proposed framework along with the Augmented Reality headset with eye tracking capabilities.

The rest of the paper is organized as follows. Background information about head-mounted eye tracking research and their real-life applications are introduced in Section 2. The proposed software architecture for large scale eye tracking analysis using super-resolution are described in Section 3. Section 4 demonstrated the robustness and effectiveness of the proposed architecture while handling conditions with background noise and illumination variations with an outdoor case study of users walking around the Tufts University campus as part of a larger navigation study administered by a team of research psychologists. The results are also evaluated using no reference image quality measurements.

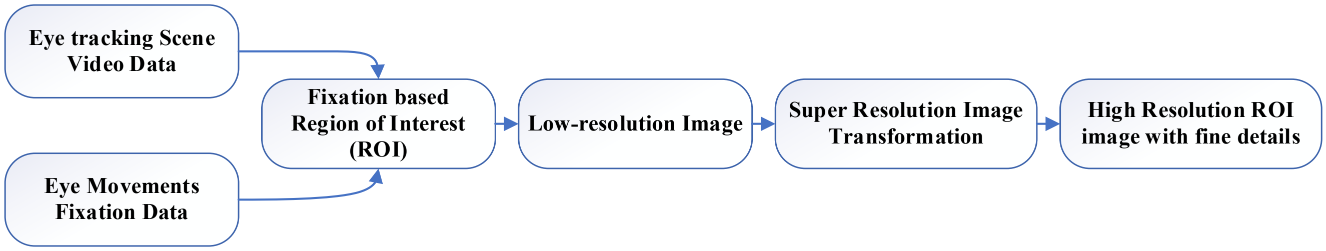

Figure 1. Flow diagram for the software solution for enhanced head-mounted eye tracking data analysis.

Furthermore, we discuss potential Augmented Reality real-life applications using our proposed framework in section 5. Finally, Section 6 draws the conclusions and future works.

2. Background Information

The motivation behind analyzing eye movements are: we direct our eye gaze to move a particular portion of the field-of-vison (FoV) into high resolution in order to gain information about fine details. Then we will know the object/region of interest, track someone's eye movements further understand the path of attention, which provides the information of what the observer found interesting or how human brain perceive information in a scene [4].

Since eye tracking sensors become easier and cheaper to use, popularity of head-mounted eye tracking technology has increased in various research fields [5], such as cognitive psychology, early child development and education, marketing and consumer science, human machine interaction, sports, medicine, virtual reality and augmented reality. The number of research publications related to head-mounted eye tracking has been increasing dramatically over the past decade. Figure 2 shows a plot of all relevant publications found through google scholar search engine [6] about head-mounted eye tracking technology.

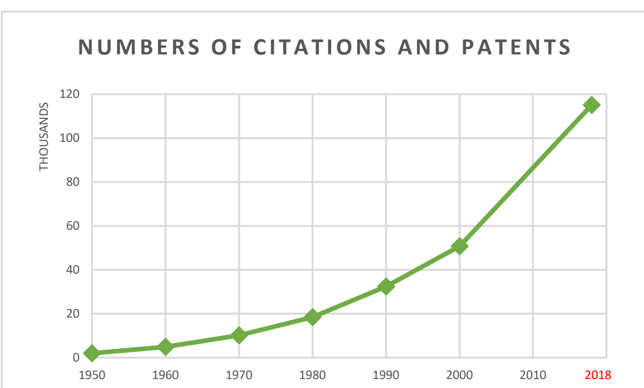

Figure 2. A plot of relevant publications found online through 1950 to 2018. The number of research articles related to head-mounted eye tracking technology has been increasing dramatically from 2010 to 2108.

Under the eye-mind hypothesis, generations of researchers are conducting human behavior hypothesis and designing possible experiments motivated by the strong relations between eye gaze points and the visual attention focus [7], especially the fixation and the overt visual attention [8]. The popular eye movements research terminologies are [9]:

1) *ROI* is short for region-of-interest, which is the specific portion of the field-of-vision that has high importance.
2) *Fixation* is a type of an eye movement where the pupil remains relatively stable over a stationary object-of-interest, which is hypothesized to correspond to the information that human brain perceives.
3) *Saccades* are rapid eye movements that are responsible for moving the pupil and between fixations.
4) *Smooth pursuit* movements is a type of eye movements tracking along with moving targets.
5) *Scanpath* contains a serious of fixations and saccades that reflects observers' viewing behavior.

Numerous eye tracking data analysis methods have emerged in the literature. Researchers come up with different solutions to analysis large-scale head-mounted eye tracking data more efficiently based on their need and focus. Wan [10] proposed a multi-level fixation based object segmentation method to help accelerate cognitive scientists figuring out what object in the recorded front scene video the participant was attending to. Kurzhals [11] proposed an interactive approach to analyzing head-mounted eye tracking data based on ROI annotation process integrating image processing technology for consumer and marketing research. eSeeTrack [12] was designed for analysis head-mounted eye tracking fixation data from recorded front scene video. It facilitates users to observe fixation patterns while manually labeling each fixation. Heatmap is a commonly used eye tracking data visualization tool [7], also known as attention map, saliency map, fixation map, and significance map. Heatmap represents durations of fixations via a semi-transparent color mask on top of a recorded video stimuli [13], which effectively reflects the importance of objects existed in the scene [14]. Scanpath combines fixation data and saccades data to create a "viewing path", in which each fixation is indicated by a circle (where the radius corresponds to the fixation duration) and saccades can be oversimplified and represented as straight lines in between fixation durations [15].

This work provides a novel software solution for enhancing head-mounted eye tracking data analysis process to retrieve fine details within ROI by utilizing state-of-art computer vision technology, deep-learning based super-resolution image transformation and video data processing. In addition, we demonstrate possible real-life applications adapting our proposed framework along with AR headset with eye tracking capabilities.

3. Proposed system

The complete flow diagram of the software solution for enhancing head-mounted eye tracking data analysis using super resolution image transformation and fixation based region of interest (ROI) extraction is showed in Figure 1.

The proposed software solution has been successfully developed and is currently being tested on a sample dataset where

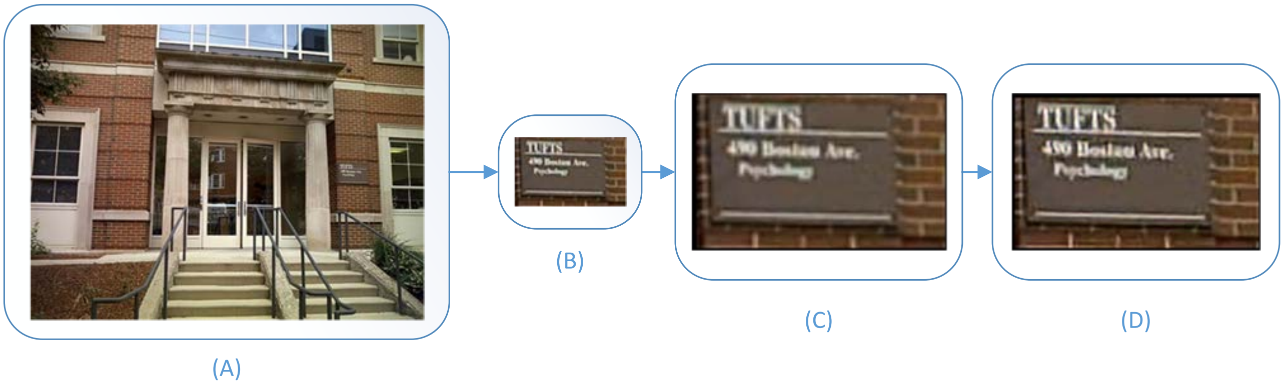

Figure 3. Enhancing partial head-mounted eye tracking data analysis using super-resolution image transform. (A) head-mounted eye tracking scene video frame; (B) fixed-size cropped region of interest (ROI) from head-mounted eye tracking recordings based on fixation location; (C) ROI low resolution image;(D)) Example result for enhanced high resolution image for head-mounted eye tracking data analysis using super-resolution image transform.

participants were walking around campus and their eye movements were captured by SMI head-mounted eye tracker (SMI-ETG 2, 60Hz). A flow chart including example results is shown in Figure 3. Detailed applied strategies are described in the section.

3.1 Fixation based ROI Extraction

We utilized fixation location in each frame provided by SMI BeGaze version 3.7. Note that additional interpolation between the generated eye movement information and recorded front scene video is required and can be resolved through eye tracker's internal clock, since the infrared camera and front scene camera run with different frequencies.

In a math conclusion as shown in Eqn. (1), video frame data and attention coordinate data is collected from eye tracking devices.

$$(X_t, Y_t, F_t) = EyeTracker(t) \tag{1}$$

Where, function $EyeTracker(t)$ is used to describe the output of an eye tracking device at time t, while (X_t, Y_t) indicates the fixation location in each video frame (F_t). A python code for this step can be downloaded from our research website: http://karen-panetta.squarespace.com/download/.

3.2 Super Resolution Image Transformation

In this step, the goal is to generate a high-resolution output image from a low-resolution input. To overcome this problem, we select to use state-of-art deep-learning based super-resolution (SR) image transform.

Deep-learning based SR has received substantial attention from the computer vision research community and has a wide range of real-life applications.

SRCNN [16] consists a fully convolutional neural network (CNN). The network takes the low-resolution image as the input and outputs the high-resolution one. SRCNN achieves a much faster speed than traditional SR methods. It represent a breakthrough in accuracy and speed of single image super-resolution.

VDSR [17] uses a very deep convolutional network inspired by Simonyan and Zisserman [18] for single image super-resolution task. The paper demonstratively verify that deeper networks give better performances than shallow one and in a much faster fashion than standard CNN.

SRResNet [19] was employed a deep residual network (ResNet), which was shown to provide a better performance with public SR benchmarks using faster and deeper convolutional neural networks.

Ledig, Christian, et al. proposed *SRGAN* [19] utilizing a generative adversarial network (GAN), which optimized some limitations of PSNR-measure focused image super-resolution and hence outperforms most state of the art for photorealistic image SR.

SRDenseNet [20] is single-image super-resolution method by introducing dense skip connections (denseNet) in a very deep CNN network, which has a good performance very fast. In this work, VDSR, SRResNet and SRDenseNet were implemented in Pytorch.

4. Experiment result and Evaluation

We first tested our proposed system architecture on an outdoor case study of users walking around the Tufts University campus administered by a team of research psychologists who focus on navigation and spatial learning ability. Visual example results are provided in Figure 4. The most recent image super-resolution algorithms, VDSR, SRResNet and SRDenseNet were implemented using image pitches cropped from real-world head-mounted eye tracking case study video data.

Moreover, image quality measurements are used to evaluate the performance of the proposed algorithms. Image quality measurements were used to provide a proof for the effectiveness and robustness of the proposed architecture. Another good reason is that automatic image quality measurement systems are known to be useful in making critical system decisions[21], hence in our scenario image quality measurements can also be considered a selector to choose the best performance super-resolution algorithms for head-mounted eye tracking data captured by different devices and filming conditions which resulting in varying video qualities.

In general, image quality measures can be classified into three categories: full-reference, reduced-reference, and no-reference [22]. Full-reference and reduced-reference image quality measurements are not suitable for evaluation in our applications because the original reference images do not exist [23]. Hence, using a no-reference image quality measure is desirable. Table 1 summarized math definition and features for no-reference image quality measurements TDMEC [21], CRME [22] and Spatial Domain Measures (AME, AMEE, EME, EMEE, LogAME [22]). Figure 5 shows the evaluation results using AME, EME and LogAME compared to the subjective human's evaluation measure, mean square opinion (MOS), where a score of one indicates best quality. ResNetSR best matches the human evaluation.

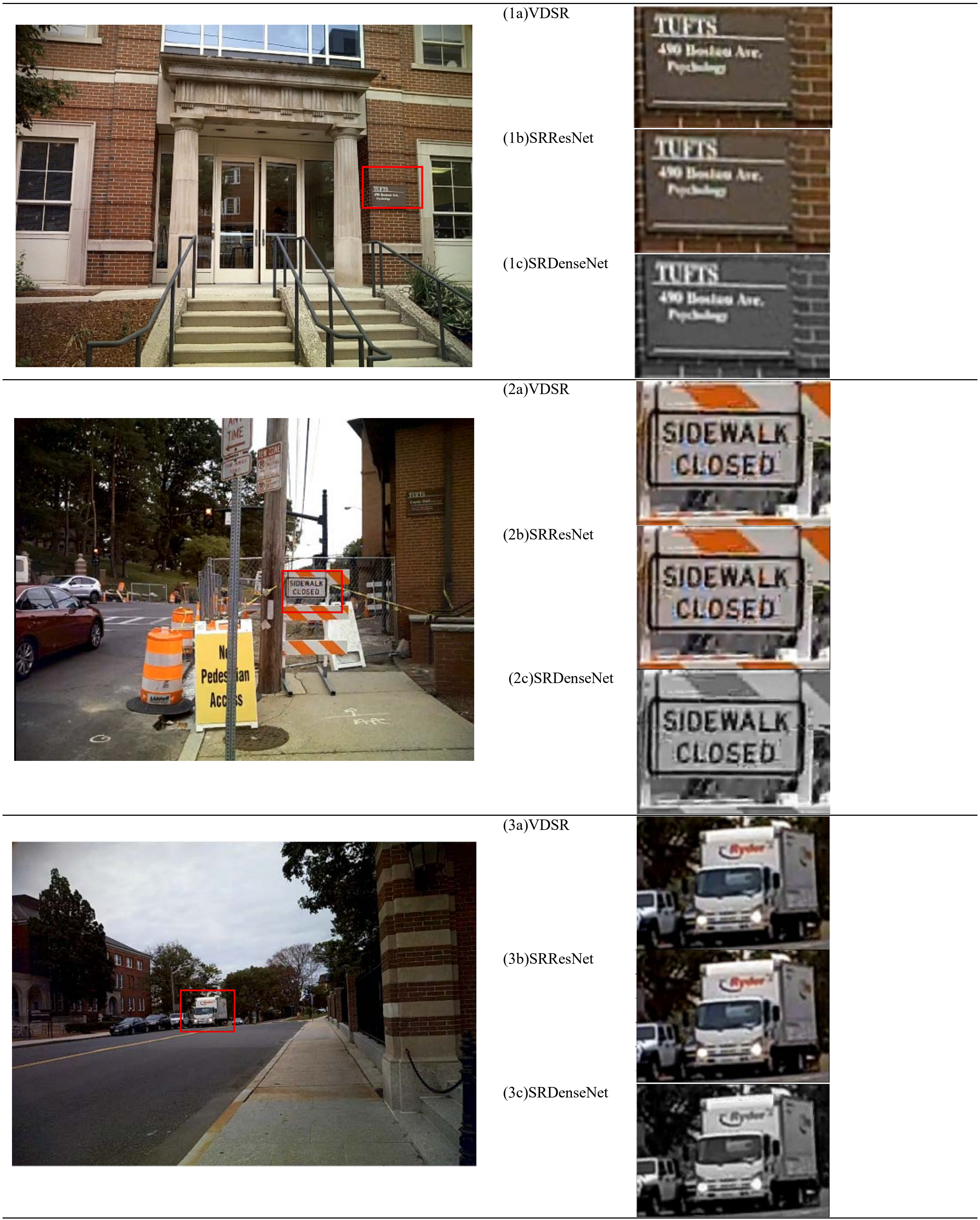

Figure 4. Example results using image super-resolution algorithms on fixed-size region-of-interests (indicated by red square), VDSR, SRResNet and SRDenseNet were implemented in Pytorch by scale 2.

Table 1. Summarization of Different Image Quality Measure

Image Quality Measure	Definition	Features
AME (grayscale)	$AME_{k_1k_2} = -\frac{1}{k_1k_2}\sum_{k_1=1}^{k_1}\sum_{k_2=1}^{k_2} 20\ln(\frac{I_{max,k,l} - I_{min,k,l}}{I_{max,k,l} + I_{min,k,l}})$	Michelson contrast based enhancement measure
AMEE (grayscale)	$AMEE_{k_1k_2} = -\frac{1}{k_1k_2}\sum_{k_1=1}^{k_1}\sum_{k_2=1}^{k_2} \alpha(\frac{I_{max,k,l} - I_{min,k,l}}{I_{max,k,l} + I_{min,k,l}})^{\alpha}\ln(\frac{I_{max,k,l} - I_{min,k,l}}{I_{max,k,l} + I_{min,k,l}})$	Incorporate entropy in AME
EME (grayscale)	$EME_{k_1k_2} = \frac{1}{k_1k_2}\sum_{k_1=1}^{k_1}\sum_{k_2=1}^{k_2} 20\ln(\frac{I_{max,k,l}}{I_{max,k,l}})$	Weber contrast based enhancement measure
EMEE (grayscale)	$EEME_{k_1k_2} = \frac{1}{k_1k_2}\sum_{k_1=1}^{k_1}\sum_{k_2=1}^{k_2} \alpha(\frac{I_{max,k,l}}{I_{max,k,l}})^{\alpha}\ln(\frac{I_{max,k,l}}{I_{max,k,l}})$	Incorporate entropy in EME
LogAME (grayscale)	$logAME_{k_1k_2} = \frac{1}{k_1k_2}\otimes\sum_{k_1=1}^{k_1}\sum_{k_2=1}^{k_2} 20\ln(\frac{I_{max,k,l} \ominus I_{min,k,l}}{I_{max,k,l} \oplus I_{min,k,l}})$	More appealing to human vision than AME
TDME (color image)	$\text{TDME}_{n} = \frac{1}{m-1}\sum_{k_1=1}^{m-1}\frac{\frac{1}{m^2-k^2}\sum_{i=k}^{m-1}\sum_{j=k}^{m-1} Mag(DCT(i,j))}{\frac{1}{m^2}\sum_{i=k}^{m-1}\sum_{j=k}^{m-1} Mag(DCT(i,j))}$	Transform domain image quality metric for color image
CRME (color image)	$CRME = \frac{1000}{k_1k_2}\sqrt{\sum_{k_1=1}^{k_1}\sum_{k_2=1}^{k_2}\left\lvert\frac{log\left\lvert I_{i,j} - \sum_{c=1}^{3}\gamma_c(\frac{I_{c1} + I_{c1} + \cdots + I_{cn}}{n})\right\rvert}{\left\lvert log\left\lvert I_{i,j} + \sum_{c=1}^{3}\gamma_c(\frac{I_{c1} + I_{c1} + \cdots + I_{cn}}{n})\right\rvert\right\rvert}\right\rvert}$	Contrast color image measure

Algorithm I described the procedure utilizing image quality measurements as an automatic selector to choose the best performance super-resolution algorithms. Head-mounted eye trackers provide front scene video recording denoted by V; and eye-gaze fixation data obtained from the two infrared cameras that monitor pupil movement, denoted by D. The fixation locations (x,y) in each frame can be extracted by the eye tracker's analysis software, denoted as $L_1^{x,y}, L_2^{x,y}, \ldots\ L_k^{x,y}$.

Algorithm I	
Input:	head-mounted eye tracking recording: V; captured eye movements data: D;
Initialization:	individual image frames $I_1, I_2, \ldots\ I_k$ extracted from V; output enhanced image frames using super-resolution $I_1', I_2', \ldots\ I'_k$; fixation location $L_1^{x,y}, L_2^{x,y}, \ldots\ L_k^{x,y}$ extracted from D

for k from 1 to K do
    Perform super-resolution algorithms on $\boldsymbol{I}_k$;
    Calculate image quality on $\boldsymbol{I}_k$;
    Look up for the maximum image quality ;
    Select corresponding $\boldsymbol{I}_k$;
    $\boldsymbol{I'}_k = \boldsymbol{I}_k$;
end	

Output: $\boldsymbol{I}_1', \boldsymbol{I}_2', \ldots\ \boldsymbol{I'}_k$;	

5. Application Discussion

The proposed system has many potential real-life applications when deploying on Augmented Reality headsets integrating eye tracking.

Table 2 Image Quality Results on example images.

	Picture 1	Picture 2	Picture 3
AME	ResNet>DenseNet>VD	ResNet>DenseNet>VD	ResNet>DenseNet>VD
EME	VD>ResNet>DenseNet	ResNet>DenseNet>VD	VD>ResNet>DenseNet
logAME	ResNet>DenseNet>VD	DenseNet>ResNet>VD	ResNet>DenseNet>VD

For military application, the proposed system can be part of an Augmented Reality (AR) system that can color overlay of long range friend/foe silhouettes. This system will be automatically running in the background and be guided by the users' eye gaze for a much narrow filed-of-vision (FoV). When a person from far away distance is detected, the ROI contains person-of-interest will be zoomed in and further enhanced; thus enemy combatants/friendlies would be detectable and classifiable.

For industry application, the proposed system can be adapted for library/museum tour. With eye gaze directed Augmented Reality devices, such as HoloLens and pupil lab add-on toolkit, the users would have a much pleasant experience while appreciating art or searching books with only a limited body movements. This application can also be used to help handicapped people viewing paintings in an augmented reality museum environment.

Broadly speaking, with the combination of real-time head-mounted eye tracking technology, augmented reality headsets and computer vision algorithm, a brand new generation of human machine interaction will be arriving in a short future.

6. Conclusion and Future works

This paper proposes 1) a novel framework for enhancing head-mounted eye tracking data analysis by utilizing state-of-art computer vision techniques. The proposed software architecture identify the area around fixation location and display an enhanced

ROI after super-resolution image transformation to the users. 2) Furthermore, we discuss and demonstrate real-life applications using augmented reality (AR) headset with eye tracking capabilities and the proposed framework. We believe the proposed system architecture is valuable in human-behavior research topics, medical diagnose, searching and rescuing application.

In the future, deep-learning models for super-resolution transform will be trained specifically for head-mounted eye tracking data. A user-friendly graphic user interface of the proposed system architecture will be created for researcher from varying backgrounds.

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