BIE-PInCS: Brain Injury Evaluation with Pupillometer based on INfrared Camera System

Filippo Bracco *IEEE Student*, Chiara Di Vece *IEEE Student*,
Luca Cerina *IEEE Member*, Marco D. Santambrogio *IEEE Senior*
Dipartimento di Elettronica, Informazione e Bioingegneria, Politecnico di Milano
{*bracco.filippo, chiara.divece*}@mail.polimi.it
{*marco.santambrogio, luca.cerina*}@polimi.it

***Abstract*— Concussion is the leading cause of death among young people under 40 years in industrialized countries, and it is fundamental to diagnose it optimally and steadily after an head trauma.**
The reactivity to light of both the pupils, the photopupillary reflex, is useful to evaluate the severity of a Traumatic Brain Injury (TBI). However, the limited capabilities of the first responders and the absence of precise quantitative assessment methods increase the complexity of TBI diagnoses for first medical responders. The aim of this project is to realize an integrated device, based on Field Programmable Gate Array (FPGA) technology, for pupillometry measurements in order to help the neurological assessment at the Point-of-Care. Thanks to the pupil detection and tracking, the automatic pupillometer allows to estimate the pupil diameter and the speed of response to light flashes, providing a quantitative information to help medical doctors. Precision and repeatability of measurements could be also helpful to evaluate subject's condition during rehabilitation phase and avoid post-trauma issues.
The proposed device guarantees real-time pupillary measurement with an infrared camera at 60 fps, with an overall speed of execution of 8.7 ms per frame (114 fps). Furthermore, thanks to FPGA characteristics, the proposed device is highly reconfigurable, portable, and power efficient.

I. INTRODUCTION

TBI is a form of acquired brain injury that can occur after an head trauma. It is estimated that 262 people out of 100.000 in Europe suffer from traumatic brain injury each year, with an average mortality rate of 10.5. Among the survivors, untreated TBI can lead to long-term comorbidities[1]. According to [2], the most common symptoms of TBI are: headache, confusion, lightheadedness, dizziness, blurred vision, tired eyes, ringing in the ears and trouble with memory, or thinking. The extension and severity of these symptoms are a good marker for the level of brain damage. The initial clinical evaluation of TBI is entrusted to the doctor who practices a careful examination of pupil reactivity with an ophthalmoscope, following a standard guideline. To date, the only universally acknowledged guideline is the Glasgow Coma Scale (GCS)[3] that estimates coma severity based on Eye (4 points), Verbal (5 points), and Motor (6 points) reactions criteria. During the execution of the test, a numerical score between 3 and 15 is assigned. GCS guarantees a prognostic predictability close to 80% [4]. However the GCS alone does not take into account the pupillary diameters and relative symmetry that, together with the motor response, represent the most significant signs for the assessment of cerebral impairment and its rehabilitation course.
In particular, the Pupillary Light Reflex (PLR), or photopupillary reflex[5], it's the mechanism that control the pupil diameter in response to the intensity of light that falls on the retinal ganglion cells of the eye, assisting in adaptation to various levels of lightness/darkness. Non-physiological pupillary reactivity, dysfunction or visible palsy can be related with a damage of the third cranial nerve, and provide a good assessment of severe TBI. The continuous evaluation of healing process is also important in order to avoid other health problems caused by TBI, e.g. chronic long-term nerve dysfunctions that can lead to patients' ptosis, strabismus, or diplopia [6].
Manual human evaluation of the pupillary light reaction can be confounded by several issues: clinicians are limited by the capability of the human eye; secondly, the examiners skills and experience level leads to a subjective accuracy in the evaluation. Furthermore, external factors including varying ambient light conditions, the distance and orientation of the penlight stimulus to the patients eye and its strength come into play [7]. These factors determine a pronounced inter-examiner variability and errors in the manual method which was repeatedly been proven to be inadequate [7]. The Infrared Pupillometry was introduced in the late 1950s [8] to solve these issues, but portable IR pupillometers have only recently become available [9].

The main contribution of this paper is the realization of an integrated, FPGA-based device, capable of sending light stimuli to the subject, recording the pupillary response using an IR Camera, and quantifying the dilation of pupils and their symmetrical response. Our system could be used both during the diagnostic phase and continuous rehabilitation. The reduced size and power consumption make it feasible to be used in medical laboratories and directly at the point of care.

The document is organized as follows: Section II describes current methodologies in the evaluation of brain injuries through pupillometric analysis; Section III describes the proposed methodology and its pros and cons against the Related Works; Section IV shows the experimental results of our tests. Finally, in Section V we briefly sum up our work and give some insights on future developments.

978-1-5386-3906-1/17/$31.00 ©2017 IEEE

II. Related works

There are several studies available in literature that demonstrate the clinical utility of automated pupillometry, for pupil health assessment and the evaluation of related pathologies. Although automatic pupillometry can be employed for different purposes, its non-invasiveness, rapidity and objectivity make it one of the best methods used to evaluate the severity of TBI [7]. The relations between TBI and abnormal pupillary response to light, were demonstrated observing two major symptoms: temporal asymmetries in pupil size (anisocoria [6]), and impaired eye movements[10]. Different studies ([5], [11]) reported that inter-examiner disagreement regarding the pupillary reaction is 39% for manual examinations, compared with 1% for automated pupillometers, confirming that the inter-rater reproducibility of exams could be enhanced using automated tools. Two different approaches were found in literature, which separately consider PLR and eye movements.

The first is the Neurological Pupil Index^{TM}(NPi) ([12], [13]) which measures pupil dimensions and reactivity to light: maximum and minimum size during test, percentage of constriction, and latencies in constriction and dilation reflexes. Each variable is compared against a normative model. The device, developed by NeurOptics Inc. to calculate the NPi, uses light flashes to stimulate the constriction reflex for 3.2 seconds, tracking the pupil at 30 frames per second (fps). A quantitative scale between 0 and 5 is calculated automatically.

The other approach [14] relies on the analysis of disconjugate eye movements, under the hypothesis that ocular motility dysfunctions are present in up to 90% of patients who suffered concussion or blast injuries. The gaze analysis approach, which considers eye saccades, fixation patterns and pupil size is studied also in [10]. In the study [14], binocular eye movements are recorded using a SR-Research EyeLink 1000, with a sampling frequency of 500 Hz. The proposed algorithm measures variance of differences between gaze coordinates for every eye, and was tested on 139 subjects to demonstrate the correlation between TBI and disconjugate eye movements. While the EyeLink system could be more precise thanks to the high sampling frequency, it is also far more costly and complex to use than the portable NeurOptics device. A comparison between the two approaches, the manual PLR and our proposed methodology is highlighted in Table I.

Both pupillometric analysis methods demonstrated to be consistent about the evaluation of eyes reactivity and severity of trauma, although through two different types of test ([7], [15], [16],[14], [10], [17], [18], [17]). All systems are non-invasive, meaning that they do not require brain like Computerized Tomography (CT) or Nuclear Magnetic Resonance (NMR). The NPi tracker has a far lower cost and a better portability compared to the EyeLink 1000, but it provides a very low sampling rate (30 fps) against 500 fps. Our device represents a trade-off in-between, with an acquisition rate of 60 fps, a good portability and a cost of components ∼300 €. The repeatability is around 99% for the NPi system against 61% of manual assessment. The repeatability of our device has to be tested yet.

TABLE I

Comparison between different type of test and tool for pupil assessment. (PLR = pupillary light reflex; ASCR = anisocoria; EM = eye movements)

	Exam type			
	NPi	**Gaze**	**Manual**	**BIE-PInCS**
Reflex	PLR,ASCR	EM	PLR	ALL
Stimulus	light	screen items	light	both
Sampling	30 fps	500 fps	n.d.	60 fps
Portable	✓	×	✓	✓
Cost	medium	high	low	medium
Repeatability	99%	n.a.	61%	to be tested

III. Proposed methodology

This section describes in detail the necessary features for a good TBI diagnosis, the employed hardware components to build our device and the algorithmic implementation of the overall project.

In order to extract features from pupils and help the medical doctors in the TBI assessment, our device will provide the following features:

- Integration of both pupillary tests (PLR/anisocoria and impaired eye movements) to obtain a broad set of features which will be fed to the classification system.
- A fast and reliable image acquisition system, capable of acquiring infrared images with a good spatial and time resolution, but maintaining a reasonable cost.
- A video and lighting system that provides stimuli to the subject which is synchronized with the recording system.
- Estimation of pupil parameters: diameter, velocity in constriction/dilation, stimulus-response latency, and percentage changes in the eye constriction.
- Creation of an output video containing tracked pupils and estimated parameters; it could be used by medical doctors in prognosis process and decision making.

The current implementation does not analyze the pupil response in real-time, hence the assessment is divided in two phases: first stimulation and video recording, then video analysis and parameters output.

In the first phase subject is asked to place the head on a head-chin stand which is necessary to guarantee a fixed position of the head. A led screen is placed at a fixed distance of 35 cm in front of them, while an Intel Realsense SR300 camera (640x480@60fps infrared stream) is placed above the screen. This fixed distance guarantees that the scale pixels-to-mm is homogeneous for all the recordings. Infrared videos are widely used to perform pupil detection, because they secure a better contrast with the surrounding iris. Stimulation video contains a black/white alternating sequence used to elicit fast pupil contractions and a second one in which the subject has to follow a set of lighted dots moving on the screen against a black background. Both stimuli and video recording are synchronized and were developed in C++ using OpenCV (www.opencv.org) and the Intel Realsense librealsense SDK. In the second phase videos are analyzed using our pupil tracking algorithm which will be described later. The output video contains the enlarged Region of Interest (ROI) of eyes with highlighted pupils along with values of clinical relevance that could be helpful to the medical doctors to diagnose TBI. The algorithm was developed using the OpenCV library in different languages and the Xilinx Vivado Toolchain for the FPGA programming. The chosen FPGA is the Xilinx PYNQ-Z1 development board, which comprises both a Linux-compatible ARM dual-core CPU and a Artix-7 family programmable logic, used to accelerate portions of the algorithm.

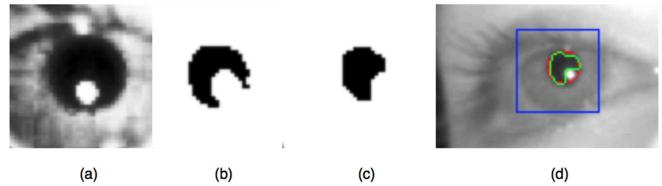

Fig. 1. Operation flow of image processing for pupil tracking. In (a) equalized ROI of eye to adjust contrast in the image; (b) after a threshold filter of intensity to individuate candidate pixels; (c) after opening and closing operations to reduce noise and to define boundaries; (d) ROI eye with highlighted the contours calculated and the enclosing circle approximating the pupil.

A. *Pupil tracking algorithm*

Pupils within image has to be identified from the eye ROI. For each frame acquired it is necessary to search for eyes and eventually to choice correctly right and left areas in the image, among several individuations. Function used to search eyes is *detectMultiScale* function from *CascadeClassifier* class, contained within OpenCV library. After that, ROI has to be processed to precisely define pupil contours using a series of common filters in image processing field. Sequence is shown in Figure 1. At first we use an histogram equalization to apply an adjustment of contrast to the image. As it can be seen pixels in pupil area have a lower intensity level, according to pupil physical features of low reflectance of infrared rays rather than surrounding tissues. So subsequently we apply to the image a threshold filter to find candidate pixels which have a lower intensity than a threshold (typically about 10% of maximum value). After that it is necessary to apply to image other series of filters of morphological transformation to allow finding contours function to work properly. In particular an opening operation followed-up by a closing operation, with a (3x3)-shaped kernel, are applied to delete any possible gaps within pupil and to erode boundary pixels of the region. Main goal of this manipulation is to define boundaries and to reduce noise. After this series of operations it can be possible to search contours in the filtered image using a procedure explained in [19], implemented with a dedicated OpenCV function. Contours vector, however, does not fit the wide area of pupil because of the corneal reflex of IR lights: this appears as a white dot in eye, frequently located within pupil. To solve this problem it is necessary to find a circle of minimum area which enclose the 2D point set of contours. As it can be seen in Figure 1 (d), pupil center and diameter can be approximate with circle just found.

B. *Method optimization*

After a performance analysis in terms of execution time, we have individuated in our method a bottleneck: the *CascadeClassifier* function, which is called for every frame that has to be analyzed, takes most of the computing time, between 60% and 70% . Due to this we tried a new different approach towards the problem to increase performance of algorithm searching ROI containing eyes only when necessary. The idea behind this new approach is to search eyes ROI in the first frame, and then using the same pupil as a tracker, adjusting the position of ROI on the center of previous eye. When tracker fails and the eye is lost *CascadeClassifier* function is called and, furthermore, left and right eyes are treated separately, allowing to call function only on half image. The fastest possible eye movements are saccades, which can reach 900°/s; hence in our experimental setup with a 60 Hz frame acquisition, each eye could have a movement of 15°from one frame to another. The maximum movement of a point on eye surface is about 2 mm considering a medium-sized eye of 16 mm diameter with the pivot center corresponding to its geometric center. Thanks to these considerations method is highly reliable using a ROI large enough to make impossible that a pupil can move outside the region between two consecutive images. We chose a region of 16 mm around each previous pupil. To manage error handling, for each frame distance between eyes is compared with the weighted average value (updated at the previous image); overcoming a distance threshold, pupil moved further away from previous position is individuated; after that the single lost eye is searched. In the output file, wrong geometric and kinematic measurement are marked with a boolean value. This solution finally allowed to reach a significant improvement in performance of algorithm: reduction of about 40% of total time execution and on average 70% per single frame analyzed, requiring the use of *CascadeClassifier* function in less than 2% of total frames.

C. *Hardware implementation*

Pupil tracking algorithm is implemented in a hardware version on a Xilinx PYNQ-Z1 board, starting from last optimized procedure. The main goal of this additional progress is to allow the fastest possible video pure analysis only for the extraction of kinematic and geometric pupil features without creation of video output. This implementation can be more suitable for long video. Main idea behind this implementation is to accelerate the application by switching part of computation from the Processing System (PS) to the Programmable Logic (PL) of device: OpenCV function calls in the pure software application are replaced with calls to an FPGA accelerator. First, a synthesizable part of algorithm has to be detected. Selected block is the part of algorithm that performs ROI image manipulation, from the equalization of histogram to the morphological transformation. Rationale behind this choice is that this part is the most suitable procedure to be accelerated on FPGA. Thanks to this considerations, design has been conducted as follows: an IP is designed using Vivado HLS tool; using Vivado it is then integrated in a design containing Zynq PS; finally overlay is exported and loaded on device to create a mixed software/hardware application. This makes possible to call FPGA accelerator from a jupyter notebook, with the high level interface of Python 3. In the application hardware computes image manipulation while the CPU manages image loading, FPGA accelerator calls, contours classification and approximation. *Image_filter* IP uses AXI Stream communication protocols and it has the same functionality of the software block; while reading the stream in *dataflow* directive, IP computes a color conversion (from 3 to single channel) and it simultaneously updates intensity histogram. Then image is equalized and both threshold filter and morphological transformation are applied. These last two steps are achieved using the *hls_videolibrary*, provided by Xilinx. According to Vivado HLS performances estimate, IP has a latency of 15872, using a 100 MHz clock frequency. Resources utilization estimate on device shows that they shall be allocated as follows: 5% of total available BRAM_18K, 5% of DSP48Es, 4% of FFs and 13% of LUTs. IP is integrated within a design containing the Zynq PS and a Direct Memory Access (DMA) manages data transfers. Once overlay is exported and loaded on device, OpenCV application for video analysis is executed in Python 3, using a jupyter notebook. In the application ROI images data are transfered to the PL instead of calling software functions in charge with image manipulation; transfer is managed using the DMA class from PYNQ drivers and two buffers containing data that has to be sent and computed image that has to be read. In this configuration the computation of an image using the FPGA accelerator takes definitely less time rather than a CPU execution using OpenCV functions; moreover performances can be improved with a proper synchronization management between PL and PS: for each cycle, overlapping in computation is maximized so that they can simultaneously compute data without dependencies from the two eyes.

IV. Experimental results

This section describes the employed experimental protocol to test our methodology and obtained results. Furthermore, it provides the performances of algorithm for different implementations, to highlight how a FPGA-based system could obtain maximum performance with a high power efficiency.

As described in Section III, our system includes an IR camera used to record the face of the subject, and a screen that generates the light stimuli. To test our algorithm we have used a 15 seconds video simulation, obtaining a raw video with 900 frames per subject. The system was first tested on a population of 10 healthy subjects. The proposed software performs pupil identification and tracking, then it saves kinematics and geometric parameters of both pupils and generates the output shown in Figure 2; it contains relevant diagnostic parameters and an highlight with a red circle of tracked pupils; furthermore in the lower part there is pupils enlargement and scale factor and both dimensions and time are indicated. It can be also seen in Figure 2 that our system is tolerant to pupil artifacts created by the light stimuli.

TABLE II

Timing of different implementations for total execution time of analysis for a 15s video and mean value of a single cycle of iterative frame analysis

Timing	**Single frame (ms)**		**Total execution (s)**
	Mean	St. Dev.	
Python	40.9	10.6	36
C++	17.7	2.6	26
Optimized search	5.1	1.7	16

Thanks to the dynamic test we obtain the variance of distance between two pupils (parameters related with impaired eye movement), while with the photopupillary reflex test we have as output maximum and minimum diameter and percentage constriction for each pupil. As it is shown in Table II, altogether BIE-PInCS takes a mean of 17.7 milliseconds with a standard deviation of 2.6 ms of analysis for each second of video (values calculated over 900 single data); in particular, using a framerate equal to 60 Hz overall time needed to analyze the previously presented stimulation video and to save outputs is over 26 seconds, against average of 40.9 ms with 10.6 ms of St. Dev. and total execution time over 36 seconds of first implementation in Python. Optimized version, instead, requires 16 seconds for total execution with average of 5.1 ms and 1.7 ms of St. Dev. per frame analyzed. It constitutes a significant reduction in terms of total execution time, of 72% and 38% compared to first and second implementation, and a reduction in time per frame analyzed over 87% and 70% respectively compared to the other versions.

TABLE III

Execution times (ms) between FPGA and PS in analysis of a single ROI (with and without needed overhead) and a frame.

Timing (ms)	**FPGA**		**PS**		**Speedup**
	Mean	St. Dev.	Mean	St. Dev.	
ROI analysis	0.366	0.008	1.168	0.004	3.19x
w/ transfer overhead	0.771	0.004			1.51x
Entire frame	1.881	0.005	3.065	0.006	**1.62x**

For the hardware implementation timing data are summarized in Table II. Execution time of application using FPGA accelerator is compared with a pure software execution on Xilinx PYNQ-Z1 device; this last one is performed by the ARM dual-core CPU. The IP is able to compute a ROI in 0.37 ms against 1.17 ms of OpenCV functions on pure CPU execution. However, to use it in a Python application with

DMA class, some additional steps has to be made: first, the ROI image has to be copied into another variable and then into the input buffer; then results has to be copied into an image variable as well. This overhead slows down the performances to 0.77 ms per ROI, but these are still better than CPU computation. Considering the entire frame, i.e. elaboration and computation of both left and right ROI, the computing time is 1.88 ms (std 0.005 ms) against 3.06 ms (std 0.006 ms) that consists in a speedup of 1.62x. In addition to image manipulation, for each frame other required operations are: loading the OpenCV image from file, checking pupil values and, if is needed, search for eye ROI. The first, in particular, takes a mean of 5.98 ms (std 0.153 ms) and depends on reading bandwidth from SD card, in which video file is stored. The latter, even if takes a mean of 73.03 ms (std 17.96 ms), it does not represent a problem because, as explained in Section III, *CascadeClassifier* calls are minimized in the analysis.

Finally, the whole 15 s video analysis application takes on average 7.87 s (std 0.10 s) using the hardware accelerator and 9,26 s (std 0,08 s) in the pure software version. The number of images analyzed per second is respectively 114 and 97.

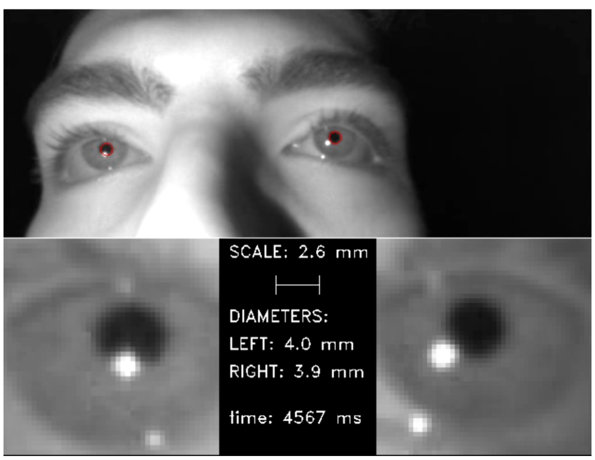

Fig. 2. Video output provided by algorithm. It contains in the upper part stimulation video with pupils tracked circled and in the lower part resized pupils ROI with relative scale factor, dimensions and time elapsed.

V. Conclusions and Future Developments

In this paper we presented BIE-PInCS, a portable device aimed at helping medical doctors in the diagnosis of traumatic brain injuries through a low cost infrared camera. The device is designed to operate either for a first trauma evaluation performed by medical first responders or in the post-acute or chronic rehabilitation phase of TBI. The advantages are for patients, doctors and hospitals. The first receive a more precise diagnosis, while when there is the need of an accurate measurement doctors and hospitals save money because they can better handle economic resources and avoid insurance costs related to eventual wrong diagnosis.

With the latest implementation we reached, as indicated in previous Section IV, a total speed-up of x4.5 compared to the first unoptimized Python version, with only 8.7ms of computation per frame, or circa 114 frames per second.

In order to achieve better performances we individuated possible future improvements. Since image loading from file video stored in a SD card is a bottleneck, it will be better to receive the data stream directly from the camera to also allow real-time analysis totally sync with stimulation. Another possible development can be achieved moving even more part of algorithm workload from the PL to the PS.

References

[1] W. Peeters, R. van den Brande, S. Polinder, A. Brazinova, E. W. Steyerberg, H. F. Lingsma, and A. I. Maas, "Epidemiology of traumatic brain injury in europe," *Acta neurochirurgica*, vol. 157, no. 10, pp. 1683–1696, 2015.

[2] N. I. of Neurological Disorders and Stroke. (2017) Traumatic brain injury informations. [Online]. Available: https://www.ninds.nih.gov/Disorders/All-Disorders/Traumatic-Brain-Injury-Information-Page

[3] F. Servadei, "Coma scales." pp. 548–549.

[4] Kameshwar and Prasad, "The Glasgow coma scale: A critical appraisal of its clinimetric properties," 1995.

[5] N. Care, D. M. Olson, S. Stutzman, C. Saju, and M. Wilson, "Interrater Reliability of Pupillary Assessments," 2015.

[6] R. Braakman, G. Gelpke, J. Habbema, A. Maas, and J. Minderhoud, 1980.

[7] J. G. Park, C. T. Moon, D. Ph, D. S. Park, and S. W. Song, "Clinical Utility of an Automated Pupillometer in Patients with Acute Brain Lesion," vol. 58, no. 4, pp. 363–367, 2015.

[8] Lowenstein and Loewenfeld, "Documenta ophthalmologica," pp. 185–448, 1958.

[9] M. D. Larson and M. Behrends, "Portable infrared pupillometry: a review," *Anesthesia & Analgesia*, vol. 120, no. 6, pp. 1242–1253, 2015.

[10] M. H. Heitger, R. D. Jones, A. D. Macleod, D. L. Snell, C. M. Frampton, and T. J. Anderson, "Impaired eye movements in post-concussion syndrome indicate suboptimal brain function beyond the influence of depression , malingering or intellectual ability," pp. 2850–2870, 2009.

[11] M. Meeker, R. Du, P. Bacchetti, C. Privitera, M. Larson, M. Holland, and et al., "Pupil examination : validity and clinical utility of an automated pupillometer," 2005.

[12] J. W. Chen, Z. J. Gombart, S. Rogers, S. K. Gardiner, S. Cecil, and R. M. Bullock, "Pupillary reactivity as an early indicator of increased intracranial pressure: The introduction of the neurological pupil index," *Surgical neurology international*, vol. 2, 2011.

[13] J. W. Chen, K. Vakil-Gilani, K. L. Williamson, and S. Cecil, "Infrared pupillometry, the neurological pupil index and unilateral pupillary dilation after traumatic brain injury: implications for treatment paradigms," *SpringerPlus*, vol. 3, no. 1, p. 548, 2014. [Online]. Available: http://dx.doi.org/10.1186/2193-1801-3-548

[14] U. Samadani, R. R. M. Eng, M. Reyes, E. Nehrbass, M. Li, E. Lamm, J. Schneider, D. Shimunov, M. Sava, R. Kolecki, P. Burris, L. Altomare, T. Mehmood, T. Smith, J. H. Huang, C. Mcstay, S. R. Todd, M. Qian, D. Kondziolka, S. Wall, and P. Huang, "Eye Tracking Detects Disconjugate Eye Movements Brain Injury Associated with Structural Traumatic Brain Injury and Concussion," vol. 556, pp. 548–556, 2015.

[15] J. W. Chen, K. Vakilgilani, K. L. Williamson, and S. Cecil, "Infrared pupillometry , the Neurological Pupil index and unilateral pupillary dilation after traumatic brain injury : implications for treatment paradigms," pp. 1–10, 2014.

[16] J. W. Chen, Z. J. Gombart, S. Rogers, S. K. Gardiner, S. Cecil, and R. M. Bullock, "Pupillary reactivity as an early indicator of increased intracranial pressure: The introduction of the Neurological Pupil index." *Neurology international*, vol. 2, no. 1, p. 82, 2011.

[17] J. Maruta, M. Suh, S. N. Niogi, P. Mukherjee, and J. Ghajar, "Visual tracking synchronization as a metric for concussion screening," *The Journal of head trauma rehabilitation*, vol. 25, no. 4, pp. 293–305, 2010.

[18] J. Maruta and J. Ghajar, "Detecting eye movement abnormalities from concussion," in *Concussion*. Karger Publishers, 2014, vol. 28, pp. 226–233.

[19] S. Suzuki *et al.*, "Topological structural analysis of digitized binary images by border following," *Computer vision, graphics, and image processing*, vol. 30, no. 1, pp. 32–46, 1985.