Modeling Pupil Dilation as Online Input for Estimation of Cognitive Load in non-laboratory Attention-Aware Systems

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***Abstract*—Dynamic changes of pupil dilation represent an established indicator of cognitive load in cognitive sciences Exploitation of these insights regarding pupil dilation as an indicator of cognitive load for attention-aware Information and Communication (ICT) systems has been impeded due to restrictions of pupil analysis to a posteriori processing and exclusion of disturbing environmental factors. To overcome these issues, this paper proposes an algorithm based on Hoeks's pupil response model, enabling online analysis of pupil dilation for the dynamic interpretation of cognitive load as an input for interactive, attention-aware systems, which outperforms state-of-the-art approaches regarding complexity, accuracy, flexibility and computation time. Beyond mathematical pupil modeling, this paper identifies Environment Illumination compensation (IC), Blink Compensation (BC), Reference Baseline computation (RB) and Onset/Offset detection (OO) as crucial fields of research for the transfer of pupillometry from the laboratory into real-life application scenarios.**

Keywords–attention-aware; behavior analysis; public displays; implicit interaction

I. Introduction

The ever increasing digitalization of our society via omnipresent, interconnected services (e.g. big data, internet of things) and devices (e.g. smartphones, wearable computers, digital cameras, etc.) has increased data production dramatically. People are flooded with amounts of information that neither are relevant nor processable, causing a constant transition of humans from actively searching, to nowadays merely defending and filtering human beings. Information overload reportedly affects humans in well-being [1][2], decision making [3] and work productivity [4][5] as well as technical systems (recommendation systems [6], information systems [7]). This widening gap between data demand and supply emphasizes the need for a new design paradigm of an attention-aware ICT that is fundamentally oriented at the respectful handling of people's cognitive resources, supplying information depending on current perception capabilities and interests.

Such an attention-aware ICT design requires the sensorial assessment and computational interpretation of individual attention mechanisms and processes as input for dynamic interaction control. Such systems could e.g. analyze the cognitive load (amount of usage of existing attention resources) of system operators in safety-relevant applications to avoid attention failures which might cause fatal consequences, be it automotive applications, healthcare or air traffic control. On the other hand, an attention-aware ICT system could measure current location of attention and level of cognitive load in alignment with task difficulty to adapt interaction modalities and information flow to current information perception capabilities, or even redirect attention to critical situations which have not been consciously perceived. The call for attention-aware ICT has been expressed several times in recent years [8][9], but today we are approaching a time in which sensory technologies and modeling capabilities might be sufficiently advanced to enable such truly user-oriented, cognition-compliant interaction designs.

This work tries to contribute the next step towards integration of cognitive parameters into dynamic interaction design via enabling an online interpretation of cognitive load (total amount of effort being used in working memory [10]) from pupil dilation on both algorithmic and system design levels.

A. Related Work

Modeling and exploiting human attention for optimization of interaction design requires the reliable and immediate assessment of current cognitive state. In the last decades, several observable expressions of individual attention and cognitive load have been identified that may serve as sensorial input, including eye gaze behavior, over overt behavior analysis, and various somatic indicators of attention. In this spectrum of multi-modal attention indicators, pupil dilation has been established in the literature as an expressive, reliable and quantifiable indicator of attention which shows promising potential to serve as an input parameter in the development of future attention-aware ICT systems [11][12].

Besides light incidence control, the pupil is also sensitive to psychological and cognitive activities and mechanisms, as the musculus dilatator pupillae is directly connected to the limbic system in via sympathetic control [13]. Since the 1960s and 70s, pupil dilation has been investigated as an indicator of cognitive activities, emotion and decision making in academic research. These research activities triggered the start of the so-called *cognitive pupillometry* focused on these *small but ubiquitous pupillary fluctuations providing a unique psychophysiological index of dynamic brain activity in cognition* [14].

As the pupil diameter is not under voluntary control, it represents a promising indicator and psychological reporter variable of internal cognitive processes. Pomplun and Sunkara [15] identified pupil dilation as a highly relevant indicator of occupied workload capacity and apply a neural-network based calibration interface and comparison of effects from cognitive workload and display brightness on pupil dilation.

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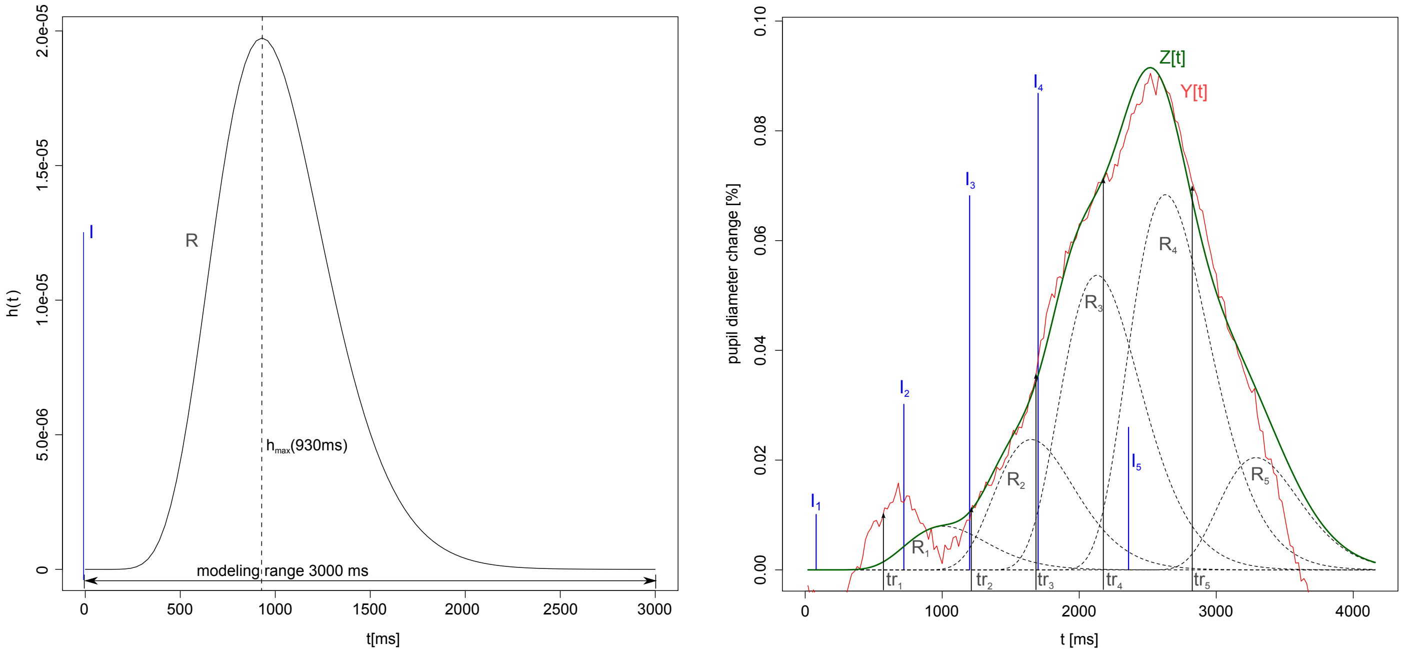

Figure 1. (a) left: Task-evoked pupil impulse response $h[t]$ (2) [19], (b) right: Modeling of pupil curve via task-evoked pupillary response (TEPR) via a linear combination of scaled and positioned attention impulse responses R_k resulting in modeling curve$Z[t]$. The impulse responses are the result of a convolution operation of instantiated impulses I_k with the impulse response h (2).

Bijleveld et al. [16] explored pupil dilation regarding strategic resource recruitment adjacent to subliminal reward cues and found that resources recruitment is independent from conscious or unconscious perception of the respective reward cue. Kang et al. [17] continued Smallwood's research [18] regarding pupil dilation as an index of overall attentional effort by controlling luminance changes, thus ruling out disturbing influences of brightness on the study results. Kang et al. successfully verified synchronized behavior in conscious versus unconscious perception of stimuli.

Besides Cognitive workload and attentional effort, the so-called task-evoked pupil response (TEPR) has found application in various other cognitive disciplines: (i) emotion & arousal [13][20][21][22][23] (ii) task switching: Katidioti et al. [24] and (iii) decision making [25][26].

This work is substantially based on two previous publications. Hoeks et al. [19] created a computational model of cognition-related pupillary behavior by modeling the TEPR as a linear input/output system whereas attentional input is represented as a sequence of attentional impulses (Figure 1), which are associated to pupillary output via a characteristic pupil impulse response $h[t]$ (Figure 1). Hoeks empirically identified the pupil impulse response $h[t]$ (Figure 1.a) to reversely compute the initial attention impulses that trigger the detected pupillary output. The position and scale of the calculated impulses represent temporal onset and amount of cognitive load whereas the distribution of the pupil dilation curve represents the respective temporal course. Mathematically, the relation between $i \leq j$ input impulses $I_i = s_i \cdot \delta[k_i]$ with scale s_i, onset time k_i and modeled pupillary output $Z[t]$ is represented via the time-discrete convolution operation, which, due to the impulse character of the input, modeling can be simplified to the following:

$$Z[t] = \sum_{i=1}^{j} (I_i * h)[t] = \sum_{i=1}^{j} s_i \cdot h[k_i - t] \qquad (1)$$

$$h[t] = t^{10.1} \cdot e^{-\frac{10.1t}{930\,ms}} \qquad (2)$$

Whereas Hoeks et al. proposed a frequency-domain-based deconvolution process to analytically deduce attention impulse input from pupillary output, Wierda et al. [27] employed a time-domain-based curve matching algorithm to compute optimal impulse and impulse response distributions. Following their empirical study, Wierda employed a fixed distribution of attention impulses every $100\,ms$ which then were scaled in a brute-force approach to best possible model measured pupillary input.

Note that Wierda added a so-called 'drift component' to his model, assuming a general decrease of pupil dilation over time to enable modeling of active pupil size reduction. Focusing on pure TEPR influences, we altered the proposed code by Wierda in the data evaluation by removing the drift component without changing any other modeling settings.

B. In this paper

In Section II, this work will propose an algorithmic approach towards the assessment of cognitive load from pupil dilation, which performance results go beyond state-of-the-art in the following key aspects (Section III):

- **Online Computation Capability** - Whereas current approaches rely on complete sets of pupil data and are only capable of a posteriori processing, this work presents an algorithm which is capable of analyzing continuous input from an eye-tracking device in real-time, enabling the immediate exploitation of pupil dilation as a fast and reliable attention indicator for a variety of devices and applications.

- **Speed** - Compared to the related work by Wierda et al. [27] the proposed approach outperforms current state-of-the-art regarding computation time.
- **Flexibility** - In contrast to comparable approaches, the proposed algorithm does not rely on fixed number and position of attention events, increasing flexibility and reducing complexity.
- **Accuracy** - While being faster and more flexible than comparable implementations, the presented approach performs at similar or not slight better levels of accuracy, based on test and training data provided by Wierda et al [27].

Furthermore, in Section IV, this paper identifies four main challenges towards the transfer of established pupillometric analysis approaches from the laboratory into real world, real-time applications employing pupil dilation as an indicator for cognitive load and input for attention-aware systems, that will be further discussed in Section V:

- **Pupillary Light Reflex** - Pupil dilation requires a very cautious analysis due to its sensitivity to environmental illumination. However, pupillary effects may be separable by their physical nature.
- **Blink Compensation** - In stable lighting conditions and fixed head settings, blinks can be erased via linear interpolation of pupil data. Yet, as blinks are often correlated to head movements (and relocations of attention) the pupil baseline may shift due to illumination changes in free movement scenarios.
- **Baseline Computation & Onset/Offset Detection** - Usual a posteriori analysis allows qualified definitions of reference baseline scores due to interpretation of the complete data set, allowing identification of onset and offset of cognitive activity. A real-time approach needs to select suitable onsets of cognitive activity without further knowledge regarding future data.

II. METHODOLOGY

The goal of the proposed developments is an iterative (frame-wise) optimization algorithm which is capable of modeling continuous data-streams of pupil dilation for online analysis of cognitive load.

Similar to Wierda's approach, we propose a curve matching optimization algorithm in the time domain in contrast to the analytic deconvolution process, as deconvolution is restricted to a posteriori processing. Yet, the proposed approach is not based on fixed numbers and locations of attention impulses, but dynamically detects the position and scale of attention impulses, optimized to best possibly match the measured pupil curve.

A. Triggering Impulses

Following Hoeks's model, the optimization algorithm is based on a list of j attention impulses $I_j(s_j, t_j)$ with scales s_i and time stamps k_i ($i \leq j$) which are set and scaled to minimize the error between the measured pupil data and the modeled pupil response. In each iteration, the error $E[t]$ between the pupil dilation signal $Y[t]$ and the current modeled curve $Z[t]$ is evaluated as to whether it exceeds a certain trigger threshold τ (see Figure 2). Such a trigger event adds an impulse $I_{j+1}(s_{j+1}, k_{j+1})$ of yet undefined scale s_{j+1} at time k_{j+1}. As the literature reports a delay between attention impulse and respective impulse response onset of $300 - 500\,ms$, impulse onset was set to $k_{j+1} = t - 500\,ms$, which showed optimal modeling performance on the applied training data.

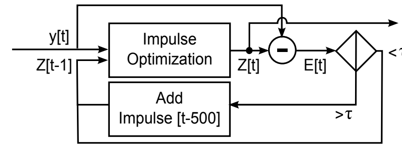

Figure 2. Pupil Modeling Algorithm

The suitable scaling of the detected attention impulses represents the most crucial challenge in the proposed algorithm. This especially covers optimization range and handling of multiple overlapping impulse responses.

B. Isolated Impulse Optimization

Hoeks's impulse response shows its biggest impacts in the range from $[k_i; k_i + 3000\,ms]$. Due to this behavior we define neighboring impulses as non-overlapping if $k_{i+1} - t_i > 3000\,ms$. In the basic case of a single, isolated impulse $i = j = 1$, the optimization algorithm needs to minimize the squared error $\varepsilon[k_1, t]$ of the accumulated error function (3) in the time range from $t \in [k_1, k_{max,1}]$ whereas $k_{max,1}$ represents the maximum peak of the impulse response curve at $k_1 + 930\,ms$. This limitation has been introduced, as a further extension of the optimization range tends to cause overcompensations of errors in the dropping slope of the impulse response which can better balanced via new attention impulses.

$$\varepsilon[k_1; t] = \sum_{t=k_1}^{t} E[t] \tag{3}$$

$$\varepsilon[k_1; t] = \sum_{t=k_i}^{t} (Y[t] - s_1 \cdot h[k_1 - t])^2 \tag{4}$$

In each iteration, the scale s_1 of the attention impulse is computed to minimize the error ($\frac{d}{ds}\varepsilon = 0$) and thus provides the optimal modeling of the observed pupil dilation curve. As soon as t exceeds the optimization window ($t > k_{max,1}$), the scale of the impulse is fixed to the last computed score, hence only current impulses ($t - k_1 < 930\,ms$) take part in the modeling process. Note that the computation of the parameters can be optimized as only the parameters of the current time-frame t needs to be computed iteratively.

$$\frac{d}{ds_1}\varepsilon[k_1, t] = 2[s_1 \sum_{t=k_1}^{t} h^2[k_1 - t] - \sum_{t=k_1}^{t} (h[k_1 - t] \cdot Z[t])] = 0 \tag{10}$$

$$s_1 = \frac{\sum_{t=k_1}^{t} (h[k_1 - t] \cdot Z[t])}{\sum_{t=k_1}^{t} h^2[k_1 - t]}, \; t \in [k_1, k_{max,1}] \tag{11}$$

$$\varepsilon(s_{i-1}, s_i) = \sum_{t=k_{i-1}}^{k_i} (Z[t] - s_{i-1} \cdot h[k_{i-1} - t])^2 + \sum_{t=k_i}^{t} (Z[t] - s_i \cdot h[k_i - t] - s_{i-1} \cdot h[k_{i-1} - t])^2 \tag{5}$$

$$\frac{\partial}{\partial s_{i-1}} \varepsilon() = s_{i-1} \sum_{t=k_{i-1}}^{t} h^2[k_{i-1} - t] + s_i \sum_{t=k_i}^{t} (h[k_{i-1} - t] \cdot h[k_i - t]) - \sum_{t=k_{i-1}}^{t} (h[k_{i-1} - t] Z[t]) = 0 \tag{6}$$

$$\frac{\partial}{\partial s_i} \varepsilon() = s_{i-1} \sum_{t=k_i}^{t} h[k_{i-1} - t] \cdot h[k_i - t] + s_i \sum_{t=k_i}^{t} h^2[k_i - t] - \sum_{t=k_i}^{t} (h[k_i - t] \cdot Z[t]) = 0 \tag{7}$$

$$K_1 = \sum_{t=k_{i-1}}^{t} h^2[k_{i-1} - t] \qquad K_2 = \sum_{t=k_i}^{t} h[k_{i-1} - t] \cdot h[k_i - t] \qquad K_3 = \sum_{t=k_i}^{t} h^2[k_i - t] \tag{8}$$

$$K_4 = \sum_{t=k_{i-1}}^{t} h[k_{i-1} - t] \cdot Z[t] \qquad K_5 = \sum_{t=t_i}^{t} h[k_i - t] \cdot Z[t] \tag{9}$$

C. Multiple Impulse Optimization Approaches

The complexity of the optimization problem increases significantly as soon as multiple attention impulse responses overlap (see Figure 1.b). There are several possible approaches to this issue, which we will discuss in more detail.

The first approach handles overlapping impulse responses consecutively, in chronological order of appearance. It optimizes the scale of the first impulse, and then iteratively computes the remaining error for optimization of overlapping impulses and impulse responses. Again, as soon as $t > t_{max,i}$, the scale s_i is fixed and impulse i is no longer part of the optimization process. This represents a very straightforward approach which allows a direct, iterative application of the principles developed for Isolated Impulse Optimization (11). However, this approach tends to create systematic errors due to the distinct independent optimization processes which manifest as continuous overestimations of the to-be-modeled curve. Due to these systematic issues, this approach has been rejected at an early stage and has not been subject to the detailed evaluations presented in the following.

The second approach avoids the problem of systematic errors caused by independent optimization processes via only optimizing the current, latest impulse response. As soon as a new impulse is added to the system, the previous impulse is fixated to the current score. This procedure also allows the direct application of the Isolated Impulse Optimization on the remaining error function, is less complex, computationally less expensive and provides significantly better results than the first approach. In the following evaluation, this model will be referenced as Single Impulse Optimization (SIO).

The third approach considers not only one but two consecutive impulses at a time, allowing a combined optimization of overlapping attention impulse responses. This approach represents a more elaborate process regarding improved modeling accuracy but also causes an increase in computation and implementation complexity.

In this case, the optimization is executed at two consecutive scale variables s_{k-1} and s_k at the same time via partial deviations of the new error function (5). Solving the partial deviations (6), (7) results in a linear equation system (7), (8) with the substitutions $K_1 - K_5$ (13 - 14). This linear equation system can be solved as visualized in (9) and (10). This optimization approach will be referred to as Double Impulse Optimization (DIO).

$$K_1 \cdot s_{i-1} + K_2 \cdot s_i = K_4 \tag{12}$$

$$K_2 \cdot s_{i-1} + K_3 \cdot s_i = K_5 \tag{13}$$

$$s_i = \frac{K_2 K_4 - K_1 K_5}{K_2^2 - K_1 K_3} \tag{14}$$

$$s_{i-1} = \frac{K_4}{K_1} - \frac{K_2}{K_1} \cdot s_i \tag{15}$$

Again, the respective parameters can be iteratively computed for the current time-frame, thus increasing computation performance.

III. Results

We employ Wierda's approach as ground truth based on the code and empirical data provided in [27] to evaluate the developed SIO and DIO algorithms.

In Wierda's empirical study, visual stimulus sequences were presented to 20 subjects at $100\,ms$ intervals and normalized pupil data is used for impulse and pupil response modeling. As some of the subject data sets did not provide any positive pupil dilation that could be modeled by the optimization approaches without the removed drift component, 5 subject data sets were removed from the dataset resulting in a final dataset of 15 subjects. The proposed algorithms were implemented in parallel to Wierda's code to evaluate our approaches regarding modeling accuracy, result complexity and computation time.

A. Accuracy

The mean squared error averaged per person for Wierda's approach as well as SIO and DIO are displayed in Table I. It can be observed that the performance of the different approaches are almost identical with slight advantages for the newly proposed methods, visualized in Figure 3. It is noteworthy, that these results were obtained employing a less complex (smaller) set of attention impulses.

Surprisingly, the more elaborate DIO approach did not provide substantial benefits in modeling accuracy, a result which was confirmed in further evaluations on continuous test and training data. This indicates that the effort for complex

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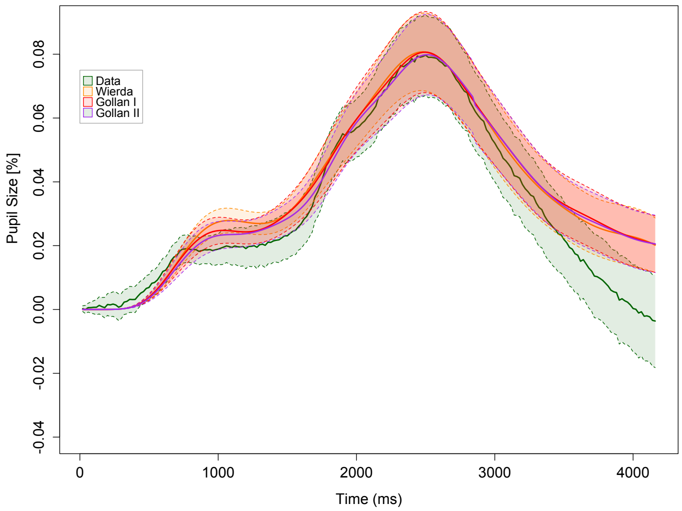

Figure 3. Comparison of modeling performance, averaged over 15 subjects. The three modeling approaches show very similar accuracy with light deviations in the range of $800 - 1200\,ms$.

TABLE I. ACCURACY

Model	MSE	average # impulses
Wierda	0.0120891	34.00
SIO	0.0118583	4.66
DIO	0.0118421	3.73

modeling of several parallel impulses is not reasonable, especially with the nonlinear increase of the associated complexity level.

B. Speed

With computation time representing a crucial aspect towards online applications, the average performance for modeling the 15 subject data sets was computed as displayed in Table II. It can be observed that the dynamic modeling approaches clearly outperform the brute-force approach by Wierda et al. without being fine-tuned towards performance optimization (iterative computation of required parameters) by a factor of 6 to 7.

TABLE II. AVERAGE COMPUTATION TIME

Model	average time [s]
Wierda	3.008
SIO	0.441
DIO	0.487

Note, that the computation times are average results for data sets of 208 instances per subject, resulting in an average computation time of $2-3\,ms$ per iteration, indicating real-time capability.

IV. Challenges towards an Online, Non-Laboratory System

To evaluate the developed algorithms in a real-world scenario, we employed long duration pupil data from an interaction field study executed at the Institute for Pervasive Computing at the Johannes Kepler University Linz. Twelve subjects wore eye tracker glasses in a half hour experiment

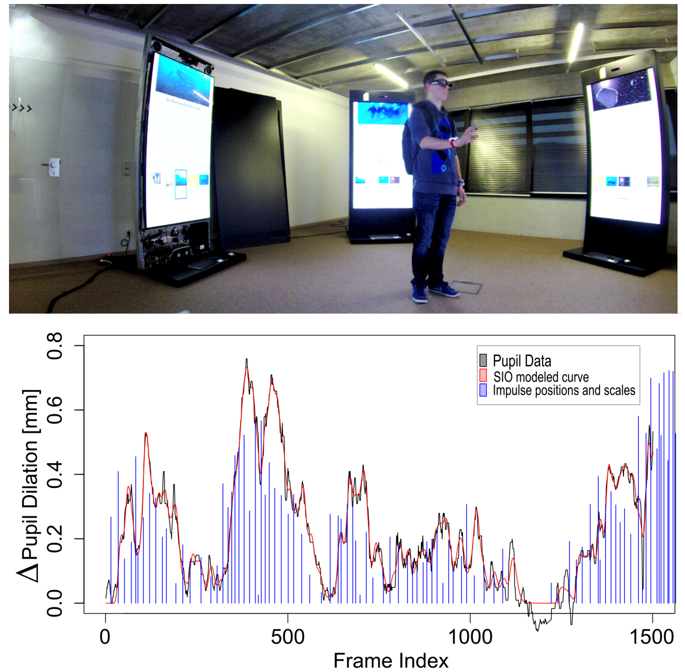

Figure 4. top: Setting of field study execution. bottom: long time scale example of curve modeling based on SIO modeling approach, showing measured pupil data, modeled pupil curve and resulting impulse positions and scales;

providing long-scale pupillary tracking data (Figure 4). The gathered pupil data was low-pass filtered to eliminate sensor noise, no further filter processes were applied.

Aiming at an online analysis of pupil dilation as a measure of cognitive load for interactive system control in real life applications poses several challenges besides the described impulse modeling. In the following, we will present four central challenges that have been identified in the research literature as well as first approaches towards the implementation of an online analysis system of cognitive load for non-laboratory environments based on a wearable eye tracker:

A. Illumination Compensation (IC)

As established in the literature, the stability of current environment illumination is the key prerequisite of pupillometric analysis, especially in non-laboratory settings. We propose to evaluate the average illumination in the subject's field of view based on a brightness analysis of the first person camera footage integrated into established wearable eye tracking sensors. For this purpose, we propose the application of the average perceived luminance [28], and thereupon interpretation of the luminance difference between consecutive frames.

As soon as detected changes in illumination brightness exceed a defined threshold, pupil analysis will be suspended until the environmental conditions have stabilized again. Perhaps in the future, the functional relation between illumination and pupil size baseline will allow the direct modeling of the reference baseline.

B. Blink Compensation (BC)

In laboratory pupillometric research, the occurrence of blinks represents less of a problem than free head movement environments. Laboratory settings usually control illumination, head orientation as well as stimuli brightness, which reduces blinks to simple interruptions of the continuous course of

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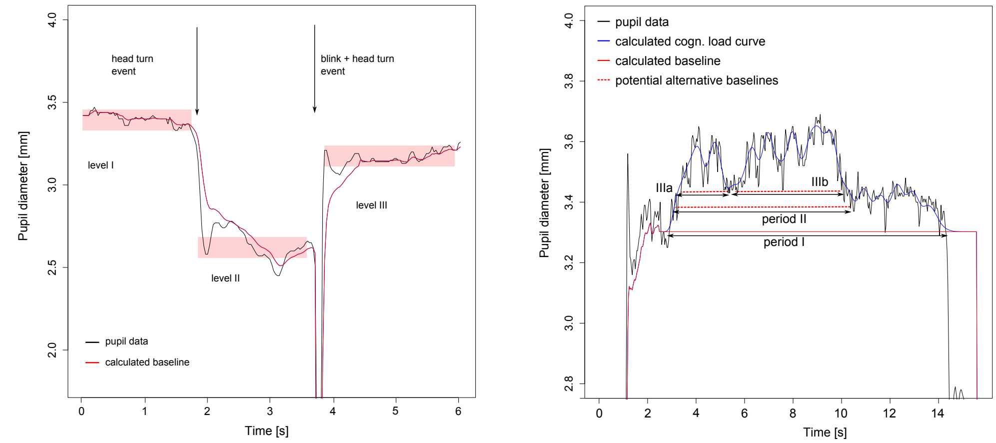

Figure 5. left: Activity and environment dependent changes of reference baseline levels; Established interpolation of missing pupil data during blinks will cause false positive modeling of cognitive activity. right: potential interpretation of period lengths and amplitudes of cognitive activity; the detection of onset and especially offset triggers allows highly different interpretations of the same data.

pupil dilation, and allow the widely established procedure of erasing blink disruptions from pupil dilation data via linear interpolation.

When analyzing empirical training data from a free head movement environment, blinks need to be considered in more detail as blinks are often correlated to head movements, thus changing the perceived field of view and exposed illumination. These changes in illumination manifest in significant baseline shifts before and after blink activities (see Figure 5), requiring a reset of reference baseline adjacent to every single blink event. Hence, we propose employing blink event detection to trigger a restart of reference baseline computation.

C. *Onset/Offset detection (OO) & Reference Baseline (RB)*

The issue of online computation capability is based on the ability of handling continuous data input streams and thus mainly in association with marking start and exit events of attention-related pupillary activity. Whereas a posteriori data processing allows the selection of adequate initiation and termination criteria of pupillary activity, continuous data processing requires qualified estimations on periods of pupillary activity.

In the proposed approach, activity onset is triggered as soon as the error between measured pupil dilation and calculated reference baseline exceeds the defined trigger threshold τ. The cognitive activity is terminated as soon as the pupil dilation falls below the onset score again. The computed averaged score at activity onset is retained as a reference baseline throughout pupillary activity. The respective reference score is averaged over the last $500\,ms$ or if situated close after a detected blink, pupil reference calculation starts right after the last blink event:

$$b[t] = \frac{1}{i_{max}} \sum_{i=0}^{i_{max}} Z[t-i] \tag{16}$$

$$i_{max} = \begin{cases} \frac{500\,ms}{fps} & \text{if } t - t_{blink} > 500\,ms \\ \frac{t-t_{blink}}{fps} & \text{if } t - t_{blink} <= 500\,ms \end{cases} \tag{17}$$

Yet, this procedure is prone to general increases of pupil dilation during an active period, which may prevent the pupil to return to its initial diameter, causing long duration mis-scalings of derived attention impulses (see Figure 5).

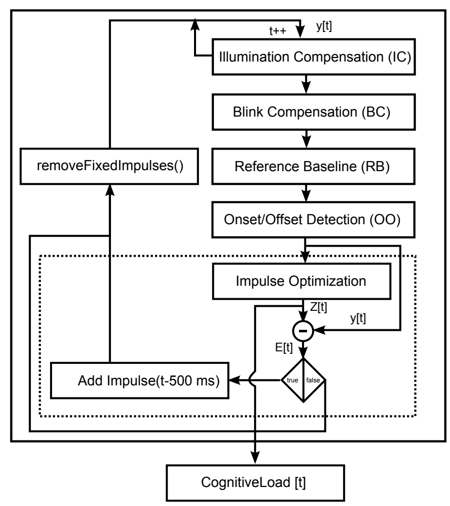

Figure 6. Structure of proposed algorithm for online analysis of pupil dilation for dynamic input for interactive systems.

D. *Proposed Process Loop*

In summary, we propose a processing loop as visualized in Figure 6, extending Figure 1. In each iteration, the captured gaze data passes the described pre-processing modules of (i) ensuring constant illumination (ii) blink detection, (iii) reference baseline computation (iv) onset/offset detection as well as the actual described curve matching algorithm.

V. Conclusion and Future Work

In this work, we have presented an algorithm for online analysis of cognitive load information from (wearable) eye tracker devices, applicable as input for online, dynamic interaction adaption to the current cognitive state of the user. This opens the door for innovative, non-laboratory attention-aware system designs and applications which are capable of adapting to current user abilities and requirements.

This work contributes a pupil modeling algorithm which exceeds current approaches in (i) online computation capability, (ii) computation performance, (iii) flexibility, (iv) result complexity and (v) has proven competitive regarding accuracy in comparison to a current state-of-the-art approach. Furthermore, this work identifies four main challenges and gives first primitive approaches towards the realization of an

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online, non-laboratory pupil analysis system, applicable for use with current wearable eye trackers and provides a means to overcome the most crucial disturbances of environment illumination, blink events as well as issues of online interpretation of cognitive pupillary activities.

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