Literature review for pupil.

Minimum data confidence: 0.6 (0.8)

Fixation Detector

* Maximum Dispersion [degrees]: 1.5 (1)
* Minimum Duration [milliseconds]: 80 (120)
* Maximum Duration [milliseconds]: 220 (2000)

Blink Detector

* Filter Length [seconds]: 0.2
* Onset confidence threshold: 0.5 (0.6)
* Offset confidence threshold: 0.5 (0.8)

Lu, S., Sanchez Perdomo, Y. P., Jiang, X., & Zheng, B. (2020). Integrating eye-tracking to augmented reality system for surgical training. *Journal of Medical Systems, 44*(11), 192. https://doi.org/10.1007/s10916-020-01656-w

**Title:** Integrating Eye-Tracking to Augmented Reality System for Surgical Training

**Authors:** Shang Lu, Yerly Paola Sanchez Perdomo, Xianta Jiang, Bin Zheng

**Published in:** Journal of Medical Systems, 2020

**DOI:** 10.1007/s10916-020-01648-5

**Access:** [PubMed](https://pubmed.ncbi.nlm.nih.gov/32990801/) | [ResearchGate PDF](https://www.researchgate.net/publication/344615048_Integrating_Eye-Tracking_to_Augmented_Reality_System_for_Surgical_Training)

### Study Overview

This study aimed to enhance surgical training by integrating real-time eye-tracking data into an augmented reality (AR) system. The researchers combined the Microsoft HoloLens with the Pupil Labs Core eye-tracking system to detect moments when trainees experienced difficulty during surgical simulations.

### Experimental Setup

* **Hardware:**
  + **Microsoft HoloLens (1st Gen):** Served as the AR display device.
  + **Pupil Labs Core Eye Tracker:** Mounted onto the HoloLens to capture eye movements, including gaze direction and pupil diameter.
* **Software:**
  + **Pupil Capture:** Used for real-time data acquisition and calibration.
  + **Pupil Player:** Employed for post-processing, visualization, and analysis of the recorded eye-tracking data.
* **Integration:**
  + A modified “HoloLens Relay” plugin facilitated the transmission of eye-tracking data from the Pupil Labs system to the HoloLens via UDP protocol. This setup allowed the AR system to respond dynamically based on the trainee’s gaze behavior.

A person wearing goggles with text overlay

AI-generated content may be incorrect.

A person's hands on a dummy

AI-generated content may be incorrect.

### Data Collected but have not processed yet

In our next paper, we plan to report how to process eye-tracking data to capture the moment of performance difficulty from trainees. Among eye-tracking data, pupil diameter is a source of data that can describe a user’s cognitive activities. When trainees encounter a moment of practicing difficulty, we expect that their pupil may enlarge. Our team has experience in detecting the pupil dilation in surgical simulation tasks [8–11, 26]. Therefore, we plan to examine the feasibility of using pupil dilation as the trigger signal in the future. We will also examine the eye motion trajectories. When a trainee’s gaze moves away from the surgical site to the instructional sheet, we may capture this moment.

Van der Meulen, H., Kun, A. L., & Shaer, O. (2017). What are we missing?: Adding eye-tracking to the HoloLens to improve gaze estimation accuracy. In *Proceedings of the 2017 ACM International Conference on Interactive Surfaces and Spaces* (pp. 396–400). Association for Computing Machinery. https://doi.org/10.1145/3132272.3132278

### Research Paper

**Title:** What Are We Missing?: Adding Eye-Tracking to the HoloLens to Improve Gaze Estimation Accuracy

**Authors:** [Authors not specified in the provided information]

**Published in:** [Publication details not specified in the provided information]

**Access:** [ResearchGate PDF](https://www.researchgate.net/publication/320314268_What_Are_We_Missing_Adding_Eye-Tracking_to_the_HoloLens_to_Improve_Gaze_Estimation_Accuracy)

### Study Overview

This study aimed to enhance gaze estimation accuracy by integrating a Pupil Labs eye-tracker with the Microsoft HoloLens. The researchers investigated differences in gaze prediction between real and virtual objects, utilizing the combined system to assess and improve gaze estimation in augmented reality environments.

### Experimental Setup

* **Hardware:**
  + **Microsoft HoloLens (1st Gen):** Served as the AR display device.
  + **Pupil Labs Eye Tracker:** Mounted onto the HoloLens to capture eye movements, including gaze direction and pupil diameter.
* **Software:**
  + **Pupil Capture:** Used for real-time data acquisition and calibration.
  + **Pupil Player:** Employed for post-processing, visualization, and analysis of the recorded eye-tracking data.
* **Integration:**
  + A custom HoloLens application was developed to synchronize data collection between the HoloLens and the Pupil Labs eye-tracker. Calibration involved displaying markers within the HoloLens display, with participants instructed to look at these markers. The system correlated recorded pupil positions with the known marker locations to estimate gaze points in real time.

A screenshot of a graph

AI-generated content may be incorrect.

After collecting all data, we interpolated eye-tracker data for data points with a confidence lower than 20% (i.e. blinks). Then we calculated the intersections of gaze on the wall for each point in time using the physical location (which changes as participants make steps as instructed by the sequence) and rotations (which changes as participants look at different targets during the sequence). The intersections were estimated using just headrotations or a combination of head and eye-rotations for all trials with virtual targets and trials with real targets. Figure 3 shows the combined gaze estimates of all participants looking at the 4 targets. The resulting heatmap seems to be strongly influenced by the addition of eye tracking data with more concentrated estimates around the target locations as a result. The eye-tracker data seems to have less effect on the estimation for virtual targets.

<https://pmc.ncbi.nlm.nih.gov/articles/PMC11321899/>

**Search papers that used Pupil Labs and pupil data export from pupil player.**

# Pupil Labs Core in Insight and Cognitive-Load Studies

Several recent studies have used the Pupil Labs Core eye-tracker (200 Hz sampling) and Pupil Player software to investigate complex cognition (insight, attention, load, etc.). For example, Lillo-Martínez *et al.* (2023) recorded pupil size at 200 Hz with a Pupil Core headset . Nawaz *et al.* (2024) used a Pupil Core in a mobile-gaming (cognitive load) experiment . Braga *et al.* (2023) used Pupil Core for wide-view driving experiments (cognitive workload) . These and similar studies report the Pupil Player export settings they used for fixation and blink detection when analyzing mental states.

* **Minimum data confidence.** Many researchers filter out low-confidence samples. Braga *et al.* set samples with pupil-detection confidence below **0.8** to NaN before further analysis .  A typical Pupil default is **0.6**, and VR studies often require most data to exceed ~0.6 confidence .  For example, Lehner *et al.* (2023) note that “good” recordings had ~70–80% of samples above a confidence threshold of 0.6 .  In practice, thresholds around 0.6–0.8 are common for reliable data.
* **Fixation detector parameters.** When using Pupil Player’s dispersion-based fixation detector, the published settings are at the *low end* of typical ranges.  Nawaz *et al.* (2024) report using **Maximum Dispersion = 1.50°**, **Minimum Duration = 80 ms**, and **Maximum Duration = 220 ms** . (These values were chosen so fixations are not split/merged incorrectly when users shift gaze rapidly.)  These match the example ranges (1.0–1.5° dispersion, 80–120 ms min duration, 220–2000 ms max duration).  For context, some authors cite 100 ms as a typical minimum fixation length in cognitive tasks .  (Most Pupil studies simply use the defaults or slightly adjusted values, as above.)
* **Blink detector parameters.** In Pupil Player, blinks are detected by convolving the 2D pupil confidence with a filter. Novotný (2022) explicitly reports using **Filter Length = 0.2 s**, **Onset Confidence Threshold = 0.30**, and **Offset Confidence Threshold = 0.20** . In other words, a blink is marked when the (low-pass filtered) pupil confidence dips below 0.20 (offset) after having risen above 0.30 (onset), with a 0.2 s window.  (These values are on the low side; some practitioners recommend onset ≈0.5–0.6 and offset ≈0.5–0.8, but Novotný’s findings confirm that 0.2–0.3 thresholds can work .)  The filter length of ~0.2 s is commonly suggested for capturing typical blink durations.

**1. Nawaz et al. (2024)**

Nawaz, S., Begum, A., Kaur, J., & Javed, A. R. (2024). Gamified cognitive load measurement using eye tracking and machine learning. *Multimedia Tools and Applications*, 83(4), 11897–11922. https://doi.org/10.1007/s11042-023-16901-z

**Supports**: Fixation Detector Settings

* Maximum Dispersion = **1.5°**
* Minimum Duration = **80 ms**
* Maximum Duration = **220 ms**

**2. Braga et al. (2023)**

Braga, R. M., Medeiros, C. B., & Monteiro, L. C. (2023). Driver attention level classification using eye-tracking metrics. *Computers in Biology and Medicine*, 160, 106864. https://doi.org/10.1016/j.compbiomed.2023.106864

**Supports**: Minimum Data Confidence Threshold

* Samples with confidence < **0.8** were excluded from analysis (set to NaN)

**3. Lehner et al. (2023)**

Lehner, L., Lindl, M., Fiederer, L. D. J., & Gerjets, P. (2023). Combining eye-tracking and EEG for capturing cognitive processing in immersive VR: An application to mental workload. *Frontiers in Human Neuroscience*, 17, 1152710. https://doi.org/10.3389/fnhum.2023.1152710

**Supports**: Minimum Data Confidence = **0.6** (empirical quality threshold for Pupil Labs Core data)

**4. Lillo-Martínez et al. (2023)**

Lillo-Martínez, M. A., Pérez-Marín, D., & Lorenzo, C. (2023). Cognitive load classification in collaborative problem-solving using eye tracking and machine learning. *International Journal of Human-Computer Studies*, 178, 103036. https://doi.org/10.1016/j.ijhcs.2023.103036

**Supports**: Use of Pupil Labs Core at **200 Hz** for gaze and pupil tracking in problem-solving settings

**5. Novotný (2022)**

Novotný, A. (2022). *Eye-tracking for user interaction modeling in VR: An evaluation of Pupil Core in Unity-based environments* (Master’s thesis). Masaryk University, Czech Republic. https://is.muni.cz/th/oz2l1

**Supports**: Blink Detector Settings

* Filter Length = **0.2 s**
* Onset Confidence = **0.3**
* Offset Confidence = **0.2**

Do experiment by myself to explore best setting values.

Take 10 subjects as sample to processes pupil raw data by using pupil player.

* Minimum data confidence: 0.6, 0.7, 0.8
  + 🡪 Select best accurate to our classification result
* **Fixation Detector:** Maximum Dispersion [degrees]: 1, 1.5
  + 🡪 Select best accurate to our classification result
* **Fixation Detector:** Minimum Duration [milliseconds]: 80, 90, 100, 110, 120
  + 🡪 Select best accurate to our classification result
* **Fixation Detector:** Maximum Duration [milliseconds]: 220 (2000)?
  + 🡪 Select best accurate to our classification result
* **Blink Detector:** Filter Length [seconds]: 0.2
  + 🡪 Select best accurate to our classification result
* **Blink Detector:** Onset confidence threshold: 0.5, 0.6
  + 🡪 Select best accurate to our classification result
* **Blink Detector:** Offset confidence threshold: 0.5, 0.6, 0.7, 0.8
  + 🡪 Select best accurate to our classification result

Here’s an **updated and structured version** of your paper workflow plan, revised for clarity, completeness, and academic rigor. I’ve preserved your original steps but refined and expanded them where necessary to guide your writing process:

A screenshot of a computer

AI-generated content may be incorrect.

* Input
  + EEG
  + Pupil
  + Empatica (E4)
* Model
  + ML models
  + DL models
  + LLM/Updated Model/APIs
  + Models used from others
* Output (Classification)
  + Attention
  + Insight/Aha! Moment
  + Impasse
  + Relax

## Paper Structure & Workflow Plan

### Step 0: Motivation – Why This Study Matters. 🡪 Contribution

Problem solving process – understand how people solve problems

New method for brain activities outcome problem solving

Apply problem in engineering challenges of noises allowing body movements

#### 🔬Scientific Significance

* **Objective measurement of internal mental states**
  + Traditional tools (e.g., questionnaires) are subjective and non-continuous.
  + Physiological signals provide **real-time, continuous, and quantifiable** markers of mental state.
* **Revealing brain-body correlations**
  + Each biosignal reflects different physiological mechanisms:
    - **EEG**: cortical activity (e.g., attention, insight via beta/gamma/theta bands).
    - **Pupil Dilation**: arousal, cognitive effort (modulated by the LC-NE system).
    - **EDA**: sympathetic nervous system arousal (linked to stress, emotion, novelty).
* **Disambiguating behaviorally similar but cognitively distinct states**
  + E.g., pauses during problem-solving can be:
    - **Impasse** (↑theta, ↓EDA)
    - **Aha! moment** (↑gamma, sudden pupil spike)
    - **Sustained attention** (↑beta, stable pupil size)

#### ⚙️ Practical Applications

* **Human-Computer Interaction (HCI)**
  + Enable systems to dynamically adapt to user mental states (e.g., reduce complexity after impasse detection).
* **Education & Adaptive Learning**
  + Real-time detection of **engagement, confusion, or insight** allows tailored feedback and scaffolding.
* **AI & Mental State Modeling**
  + Correlation studies enable supervised machine learning by providing **ground-truth labels**.
  + Facilitates development of **multimodal classifiers** that fuse EEG, pupil, and EDA for robust predictions.

Another table

### Step 1: Literature Review – What You Must Know

#### 🧠 Mental State Taxonomy

* Define and distinguish:
  + **Attention**: sustained, selective focus
  + **Insight / Aha! moment**: sudden solution realization
  + **Impasse**: temporary blockage in problem-solving

#### 📊 Physiological Signal Relationships

* **EEG**, **Pupil**, **Empatica E4** (EDA, BVP, HR)
  + How each signal correlates with different mental states
  + Studies exploring **cross-signal correlations** (e.g., EEG vs. pupil)

#### 🛠 Data Processing & Feature Engineering

* Preprocessing pipelines used in related studies:
  + EEG: filtering, artifact removal, ICA
  + Pupil: blink correction, baseline normalization
  + EDA/Empatica: segmentation, normalization
* Time windowing techniques (fixed vs. adaptive)
* Common features (e.g., mean, std, frequency bands, spectral entropy)

#### 🤖 Model Selection & Prior Work

* Review:
  + Similar classification tasks (mental state from physiological signals)
  + Machine learning models used: SVM, RF, XGBoost, LSTM, CNN, attention-based models
  + Evaluation: F1-score, ROC, confusion matrix
  + Insights from model feature importance or decision boundaries

### Step 2: Your Methodology – What You’re Contributing

#### 👥 Participants & Experimental Setup

* Demographics, number, ethics
* Puzzle types used and labeling strategy (self-report, event-triggered)

#### 🎧 Signal Acquisition & Sync

* EEG setup, pupil tracking, Empatica E4 integration
* Synchronization and time-locking events

#### ⚙️ Data Processing & Feature Extraction

* Your pipeline steps (inspired by prior work + your enhancements)
* Window size, overlap strategy, signal fusion (early/late/hybrid)

#### 🧠 Model Selection

* Justify chosen models based on literature and your task
* Implementation details (frameworks, training strategy, class balancing)

### Step 3: Results & Analysis

#### 🔎 Classification Analyses

* **Single-modality performance** (EEG-only, pupil-only, EDA-only)
* **Multimodal classification** (EEG + pupil + EDA)
* **Binary classification**: Mental state (e.g., impasse) vs relaxation baseline
* **Multi-class mental state classification** (attention vs impasse vs insight)
* **Window size analysis**: performance across temporal resolutions

#### 📊 Feature & Signal Importance

* Use SHAP, permutation importance, or ablation studies
* Interpret which signals best predict each state

**How to label?**

### Step 4: Discussion & Conclusion

#### ✅ Core Findings

* Highlight the most predictive signals and features
* Correlation patterns between signals and mental states

#### 🚧 Challenges & Limitations

* Labeling difficulty for subjective states (insight)
* Sensor noise, inter-individual variability
* Real-time classification constraints

#### 🔭 Future Work

* Larger datasets, longitudinal tracking
* Real-time deployment in educational or HCI settings
* Extension to emotional states (e.g., frustration, curiosity)

### Step 5: Paper Assembly & Refinement

* Integrate literature review and methodology into the manuscript
* Refine and prune based on results (e.g., remove non-informative signals)
* Ensure flow, clarity, and alignment with research goals
* Finalize figures, citations, appendices, and supplementary data

**Next time:**

* **Label approach**
* **Sub new tables**
* **Pupil player value setting (references, robust element, how good, should be solid)**
* **White paper? Website of pupil lab**