Chapter 3

Automated Vector-Based Gaze Analysis for Perception-Action Diagnostics

Ralf Kredel, *André Klostermann* and *Ernst-Joachim Hossner*

University of Bern, Switzerland

Abstract

Research on decision making and perception-action coupling in sports often employs video-based mobile eye-tracking systems. However, technical and methodological limitations of currently available commercial systems impair the utilization of those systems according to scientific standards so that gathered data should be interpreted with caution. In this chapter, an automated vector-based system architecture overcoming such limitations is introduced and its performance and accuracy are evaluated. Furthermore, two application scenarios are outlined and, finally, possibilities for future extension are discussed.

Keywords: Gaze analysis, vector-based eye-tracking, perception-action coupling, decision making, sports, implementation, automation, evaluation

Introduction

Over the last decade, research on expert performance has focused on the identification of perceptual-cognitive skills underlying anticipation and decision making in sports (for a review, see Mann, Williams, Ward, & Janelle, 2007). In this vein, two approaches have prevailed that either indirectly or directly examine differences in gaze behavior in video-

---

* University of Bern, Institute of Sport Science, Alpeneggstr. 22, 3012 Bern, Switzerland. Email: ralf.kredel@ispw.unibe.ch

based anticipation tasks. On the one hand, potentially crucial visual information is spatially or temporally occluded for testing effects on decision making. On the other hand, gaze behavior is directly analyzed by recording eye movements, which are mapped onto a head-fixed scene camera image (for an overview see Farrow & Abernethy, 2007).

However, a surprisingly small number of studies, e.g. Mann, Abernethy, and Farrow (2010), has pursued the second approach of analyzing gaze behavior with mobile eye-tracking equipment in real world settings so far, albeit the setting's adjacence to reality is considered crucial with respect to studying perception-action coupling (Williams, Davids, & Williams, 1999, p. 170). This deficit might be attributed to technical and methodological limitations. First, most mobile eye-tracking systems only allow for very restricted mobility since participants either are directly connected to recording devices containing heavy battery packs or need to stay close to a desktop computer, as the length of cabling is limited. Second, spatial accuracy of the results is low since the rater-based mappings of the gaze positions to areas of interests are more rough guesses than objective measurements, and errors are further amplified in dynamic situations by inevitable eye tracker movements with respect to the eye. Third, because of the imperfect collocation of the eye and scene cameras (parallax error: Evans, Jacobs, Tarduno, & Pelz, 2012), only a limited depth range is mapped accurately on the scene video stream so that, if not specifically accounted for in the algorithm, spatial analyses of gaze shifts from peripersonal to extrapersonal space should be considered as highly challenging. Fourth, most mobile eye-tracking systems only offer a low temporal resolution, so that thorough analyses of gaze kinematics seem impossible, since saccadic eye movements are fast and highly dynamic (Nyström & Holmqvist, 2010). Fifth and finally, due to the large amount of manual frame-by-frame analysis involved in video-based methods, most studies comprise a small number of participants and trials only, raising the question whether reliability for generalization is assured to a sufficient degree.

Consequently, in order to overcome the problems just mentioned, a technological and methodological shift seems to be needed which is based on measuring gaze behavior by light-weight and non-obstructive eye-tracking systems with high temporal and spatial resolution not suffering from parallax error, while keeping both, stimuli and responses, similar to the real-world demands. Furthermore, in order to guarantee data quality, regular automated checks during data collection need to be implemented in the eye-tracking software, informing the experimenter about the current calibration quality and indicating a need for recalibration. Last, the highly subjective and tedious manual data analysis needs to be replaced by an automated, objective data-to-stimulus assignment process, which would facilitate the analysis of high numbers of participants and trials. Therefore, in the following, the implementation of an eye-tracking and gaze-analysis system fulfilling these criteria will be introduced. Afterwards, experimental system evaluations, application scenarios and possibilities for future extensions of the system will be described.

System Design

To allow for a complete automation of the eye-tracking and analysis process, a methodological shift from video-based capturing to a mathematical representation of gaze seems appropriate (as already proposed by Duchowsky, 2003). With this shift from the direct

mapping of the gaze orientation to a gaze position in a video image – as done in classical mobile eye-tracking systems – towards a vector-based representation of gaze, the parallax error, which quantifies the dependence of the measurement's spatial accuracy on the gaze depth relative to a calibration plane, can be eliminated. This is due to the change from determining the gaze position in a video frame towards a mapping procedure where the calculated gaze vector is intersected with the positions of various objects of interest in different depth ranges. In this alternative approach, because of the collocation of the eyeball center and the origin of the gaze vector, different object distances do not exert influence on spatial accuracy of the gaze any longer. Beyond, the mathematical representation makes an additional scene camera dispensable for analysis, opening up the possibility to further reduce the overall weight of the eye-tracking system and allowing for more suitable gaze analyses in highly dynamic sport settings.

More specifically to our setup, the implemented eye tracker hardware consists of a reduced version of the EyeSeeCam developed by Kohlbecher, Bartl, Bardins, and Schneider (2010). Instead of having a scene camera and calibration lasers, the eye tracker is only composed of a single infrared camera, mounted directly on the goggles' frame, which renders the system very lightweight (Figure 1, left panel). Due to the camera's Firewire interface, in its current version, participants need to wear a small bum bag with an optical repeater (UniBrain Glass Optical Fiber Repeater-800), necessary for the extension of the Firewire connection to the control laptop, and its power supply.

Figure 1. Left panel: Lightweight, monocular EyeSeeCam. Right panel: Extracted pupil center and overlaid eyeball model.

From a mathematical point of view, the gaze vector originates at the center of the eyeball and its orientation is expressed by a rotation matrix, a rotation vector or a quaternion, with respect to a neutral gaze orientation (as already proposed by Haslwanter, 1995). This orientation is calculated by measuring the displacements of the extracted pupil center in the video image plane with respect to a neutral position gazing straight ahead and by using a model of the eyeball, which maps these planar displacements to orientation angles.

As eyeball size and position with respect to the eye tracker cameras are individually different, a calibration routine for the eyeball model is needed in order to estimate these parameters. In our case, this parameter estimation is done by the calibration routine of the EyeSeeCam software (as described in-depth by Kumar, Kohlbecher, & Schneider, 2009), which runs on a control laptop (MacBook Pro, OS X). By processing the obtained video stream (i.e., edge detection, binarization, ellipse fitting and center estimation) and analyzing the planar displacements of the pupil center over a calibration recording, in which the participant needs to repeatedly fixate five different target dots with 8.5° horizontal and

vertical spacing (five-point-calibration pattern), the scale factors of the eyeball model are estimated (Figure 1, right panel). After successful calibration, the EyeSeeCam software provides horizontal and vertical eye rotation angles in real-time. Additionally, the calculated angles are mapped on two ports of an analog output card as voltage signals, which can be accessed by third party devices, e.g., by a data acquisition system (DAQ). As the EyeSeeCam system was developed with the real-time control of a gaze-driven camera in mind, low latency of the system was an important design requirement (Schneider et al., 2009). Therefore, the latency from camera input to extraction of the eye rotation angles amounts to 5ms only, while the overall latency from camera input to analog output of the eye rotation angles is reported to be less than 16.5ms (Kohlbecher et al., 2010). In our setting, this low latency is particularly important when taking possible gaze-training applications into account or applications with gaze-driven visual stimuli.

In order to calculate the origin and direction of the gaze vector with respect to a world or laboratory frame of reference while allowing for unconstrained head movements, not only the individually varying neutral gaze orientation and the current eye orientation need to be tracked during calibration and measurement, but also the position of the eyeball's center in space. Assuming that the eyeball center is rather rigidly positioned inside the head and that the eye-tracking goggles remain rigidly attached to the head, a motion capturing system tracking the goggles' position and orientation suffices to fulfill this task. Ideally, the system would support real-time streaming of the acquired data to allow for an easy-to-use online calibration routine without restriction of the head position during the calibration phase. In our setup, we use a 10-camera Vicon T20-System (Oxford Metrics) for this tracking task. Equipped with an additional DAQ interface, which synchronously samples the output ports of the eye tracker's analog card, the Vicon system provides the possibility to access kinematic marker data and analog data in real-time via Ethernet socket connections. Eye rotation angles as well as the goggles' position and orientation and, optionally, further body kinematics are accessible in real-time and can be processed online, e.g., by a Matlab (The Mathworks) script or other custom software. In our case, we implemented a Matlab-based user interface, which simplifies the management and storage of the individual neutral gaze orientations, controls the calculation of the gaze intersection point with the projection screen and renders a graph containing these gaze points on the projection screen. Details of the system's functionality and of the mathematical calculations can be found in Kredel, Lienhard, Klostermann et al. (2011).

Constrictively, one has to mention that assuming a rigid attachment of the eye-tracking goggles to the head is only valid in static situations and as long as no manual touch alters the goggles' position with respect to the head. This precondition, however, can inherently not be assured during normal handling and even less during highly dynamic sport tasks. Therefore, the proposed eye-tracking system needs to constantly monitor the validity of the calibration and eyeball center position with respect to the measured position and orientation, ideally by automated tests during data collection (between experimental trials).

Due to our system's online capabilities, we are able to display stimuli with respect to the current head position and orientation on a large-scale projection screen, which is used to display the five-point-calibration pattern or to adjust the individually varying neutral gaze orientation. As we are also able to display the intersection point of the projected gaze vector with the projection screen (*screen gaze*), we can ask the participants to fixate specific dots on the calibration pattern while evaluating the distance of the screen gaze to the point of the

calibration pattern, in other words, we can manually monitor the current accuracy of the system and decide whether recalibration is necessary or not. As this, until now, is still a manual process, we additionally use static fixation points between experimental trials, which gives the opportunity to automatically quantify movements of the goggles with respect to the head (*slippage*) and to calculate correction matrices to account for this systematic error on a trial-by-trial basis. Summing up, the basic functionality of the implemented system can be characterized as follows (see Figure 2): In order to calculate a gaze vector in space, the current orientation of the eye with respect to an individual neutral gaze orientation needs to be tracked, which is done by the EyeSeeCam. To allow for unrestricted head movements, a synchronous acquisition of the eyeball center's reference frame is necessary, specifying its position and orientation in space with respect to a global frame of reference. This can be done with a synchronous acquisition of the eye-tracking goggles' position and orientation by a Vicon system. An extension of this head tracking functionality by additional markers for, e.g., a biomechanical model of the moving participant allows for synchronous recording of gross-scale motion, which, in turn, is relevant to detect movement initiation times or to calculate additional measures related to the motor response. As, in practice, the goggles are not rigidly fixed to the head, online verification of the current tracking and calibration accuracy and, ideally, automated correction routines to account for any slippage have to be implemented between experimental trials.
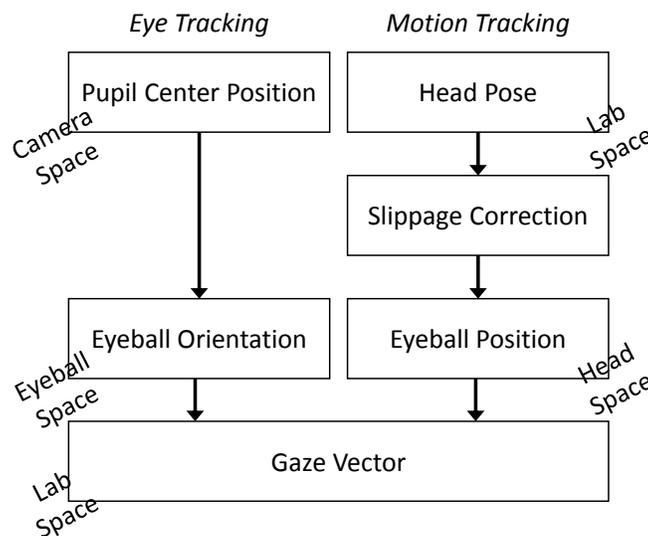

Figure 2. The process of the gaze-vector calculation. The eye tracker records the pupil center in camera space. On the basis of the parameters acquired during calibration, the eye-tracking system calculates eye orientation angles with respect to the eyeball center. By assuming that the eyeball center is rigidly positioned inside the head (or at least that the slippage can be estimated), the head pose in space, simultaneously tracked by the motion capturing system, and a fixed translational offset fully specify the current eyeball position and orientation in lab space. Combined with the eye orientation angles, a gaze vector in space can be calculated.

Evaluation of Performance and Measurement Accuracy

Since the quality of the EyeSeeCam parameter estimation method was unknown and additional error factors for the gaze estimation could have originated from the integration of the tracking system, the overall system's accuracy had to be determined. To this purpose, different calibration and tracking scenarios were analyzed in four experiments with 12 (6 females, 6 males) sport science students of the University of Bern. In the first experiment, effects of the fixation sequence and of the overall calibration duration on the accuracy of the parameter estimation were addressed. With the second experiment, effects of different eye-tracking camera positions on gaze accuracy were checked, and the third and fourth experiment aimed at determining the accuracy of the recalibration procedure and the dynamic accuracy of the gaze vector.

In all experiments, participants were positioned at 3 meters distance from the large-scale projection screen (3 x 2 meters) wearing the EyeSeeCam with additional retroreflective markers tracking its position and orientation in space (see Figure 1, left panel). Participants were instructed to fixate the five displayed dots, which were projected with an 8.5° inter-point distance onto the screen based on the current head pose (five-point-calibration-pattern). As dependent variables, the mean directional errors as well as the mean RMS error of the screen gaze versus the point positions of the displayed 5-point calibration pattern over a 30 seconds measurement interval subsequent to the calibration period were calculated. Manipulation order was counter-balanced and participants repeated each measurement ten times.

In the first experiment, the duration of the calibration routine as well as the sequence order was manipulated. The duration of the calibration routine before parameter estimation was started lasted either 3000 or 6000 valid fixation samples, i.e., measurement points with eye rotation speeds smaller than 5°/s. In sequence "short", the order of fixations was always from the middle dot to the outer dots in a counter-clockwise succession whereas in sequence "long", participants were instructed to fixate the dots in an order, which induces longer saccades compared to the other sequence (see Figure 3).
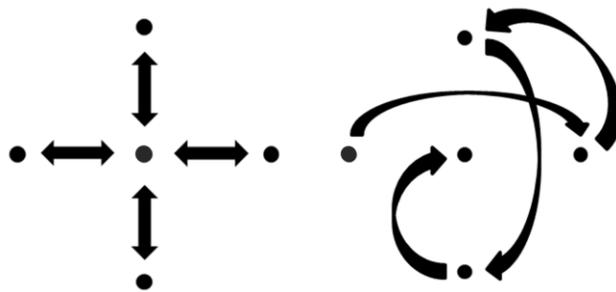

Figure 3. Left panel: Sequence "short", inducing short saccades. Right panel: Sequence "long", inducing long saccades.

The lowest error scores were found for the 3000-samples-short-sequence condition (see Figure 4; $M = 0.86°$, $SE = 0.01°$) with a magnitude, which is comparable to other mobile eye-tracking systems (manufacturer data sheets usually state about 0.5°-1.0° accuracy). However,

a great proportion of this error originated from a systematic error in the estimated gaze position. This systematic error could be caused by a mismatch of the actual and measured screen positions, by an offset in the display of the calibration stimuli or by the limiting fact, that the current system configuration used the left eye for gaze estimation only, while the dominant eye of 65-70% of the population is the right eye and therefore might dominate the current gaze location (Roth, Lora, & Heilman, 2002). Irrespective of the actual cause, correcting for this systematic error by subtracting the average directional offset over all conditions, resulted in an RMS accuracy of 0.29° (SE = 0.01°) for the 3000-samples condition (short: M = 0.28°, SE = 0.01°; long: M = 0.30°, SE = 0.01°) and of 0.36° *(SE* = 0.02°) for the 6000-samples condition (short: M = 0.35°, SE = 0.02°; long: M = 0.37°, SE = 0.02°). Consequently, due to the smaller remaining errors, the 3000-samples-short-sequence condition was chosen for future calibrations.
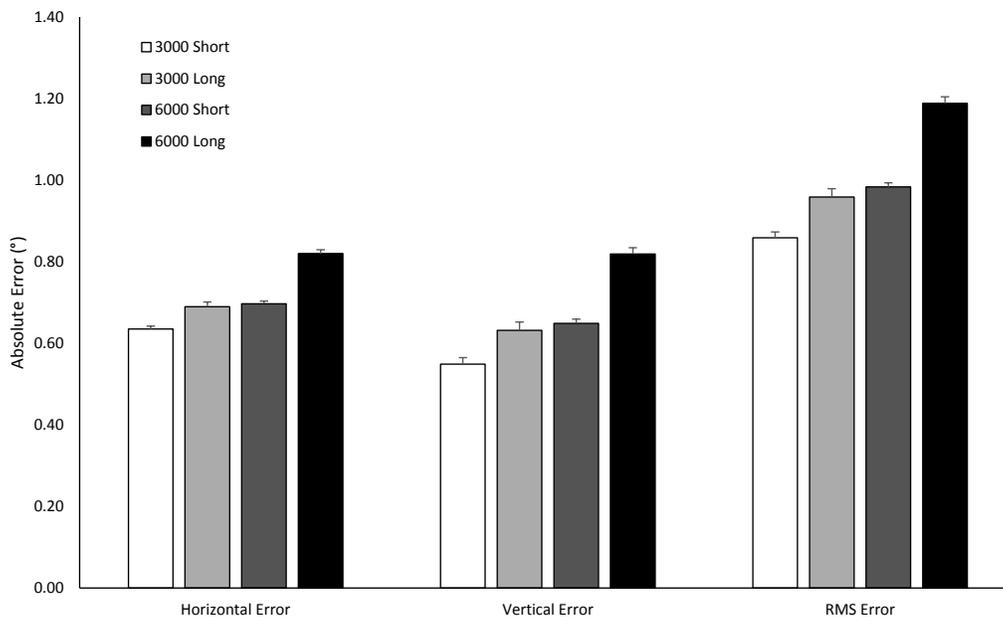

Figure 4. Absolute gaze error (horizontal, vertical and RMS; *M* and *SE*) as a function of two durations of the calibration routine (3000 vs. 6000) and two sequences (short vs. long saccades) in Experiment 1.

In the second experiment, the position of the eye-tracking camera was manipulated, putting the pupil center during neutral gazing either into the center, into the upper third or towards the right of the video frame. This manipulation accounts for possible effects of position-dependent lens distortions onto the accuracy of eye orientation estimates. Even if horizontal and vertical components differ for the right position of the camera compared to the two other conditions (see Figure 5), only minor RMS accuracy differences between different eye-tracking camera positions with respect to the neutral gaze direction were found, indicating that – as long as the pupil is roughly centered in the video stream – the effect of lens distortion on gaze accuracy seems to be negligible.

In the third experiment, it was analyzed how slippage of the goggles affects gaze estimation accuracy and to what extent an automated recalibration procedure reduces the resulting error. In order to simulate the effects of the goggles' slippage, after the initial

calibration, participants were asked to shift the goggles either up or down with respect to their eyes in such a way that the pupil was still completely visible over the 5-point calibration routine. Afterwards, participants had to fixate a static dot centered on the projection screen. Applying a dispersion-based fixation algorithm (cf., Nyström & Holmqvist, 2010), the longest fixation during the display of the dot was extracted and the difference vector between the dot and the current fixation location, the *slippage vector*, was calculated, which, in turn, was used to calculate a rotation matrix. By applying this matrix, the neutral gaze orientation matrix could be corrected in order to adjust the following gaze estimates, which were used to calculate the remaining absolute horizontal, vertical and RMS errors. After a further calibration recording, the shifting process was repeated to the opposite direction.
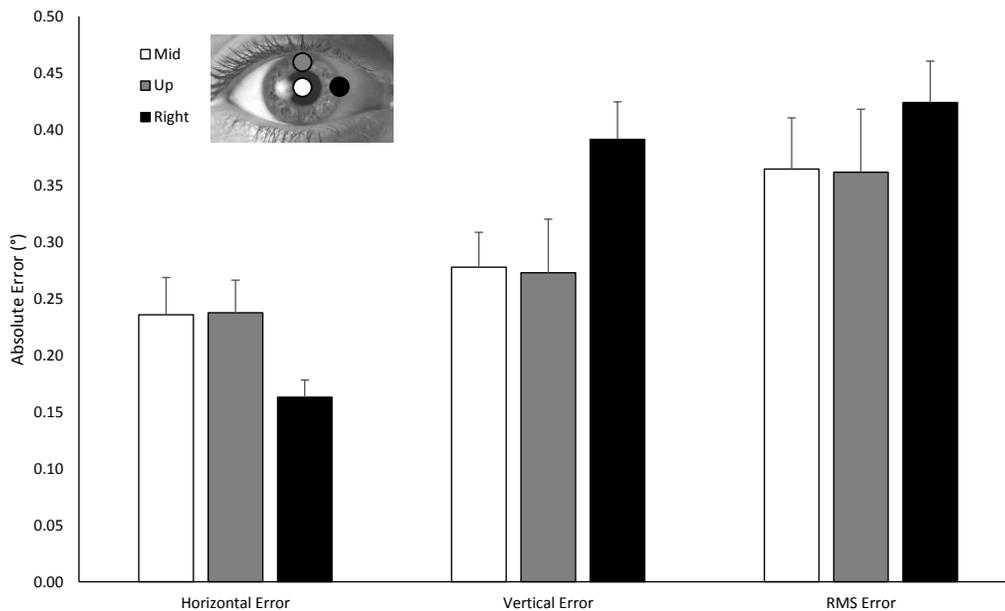

Figure 5. Absolute gaze error (horizontal, vertical and RMS; *M* and *SE*) as a function of camera positions with respect to the eye (Mid, vs. Up vs. Right) in Experiment 2.

The mean arc length of the slippage vector for the "Up"-condition was 15.95° (*SE* = 1.48°) and 25.04° (*SE* = 1.07°) for the "Down"-condition, while the horizontal slippage was 2.47° (*SE* = 0.27°) and 0.85° (*SE* = 0.45°), respectively. After applying the recalibration routine, the residual RMS errors were 0.57° (*SE* = 0.06°) for the "Up"-condition and 0.66° (*SE* = 0.06°) for the "Down"-condition (Figure 6, see also the horizontal and vertical errors). In sum, the recalibration routine can be classified as successful, even if the current implementation does not reach the accuracy of an initial calibration. However, as time consumption for fixating a static dot between experimental trials is minimal and sometimes even a standard procedure, the implemented slippage correction proofs its feasibility for application, especially as the resulting accuracy is well inside accuracy ranges reported for commercial mobile eye-tracking systems.

In the fourth experiment, it was analyzed how movements of the participants affect measurement accuracy. For this purpose, after calibration of the eye tracker, participants were asked to perform either running or jumping moves on the spot for 30 seconds while fixating

static dots displayed on the projection screen. Errors were analyzed before and after the movement interval. Descriptively, the mean RMS estimation error increased from 0.16° (*SE* = 0.03°) to 1.28° (*SE* = 0.09°) after the motion phase (Figure 7).
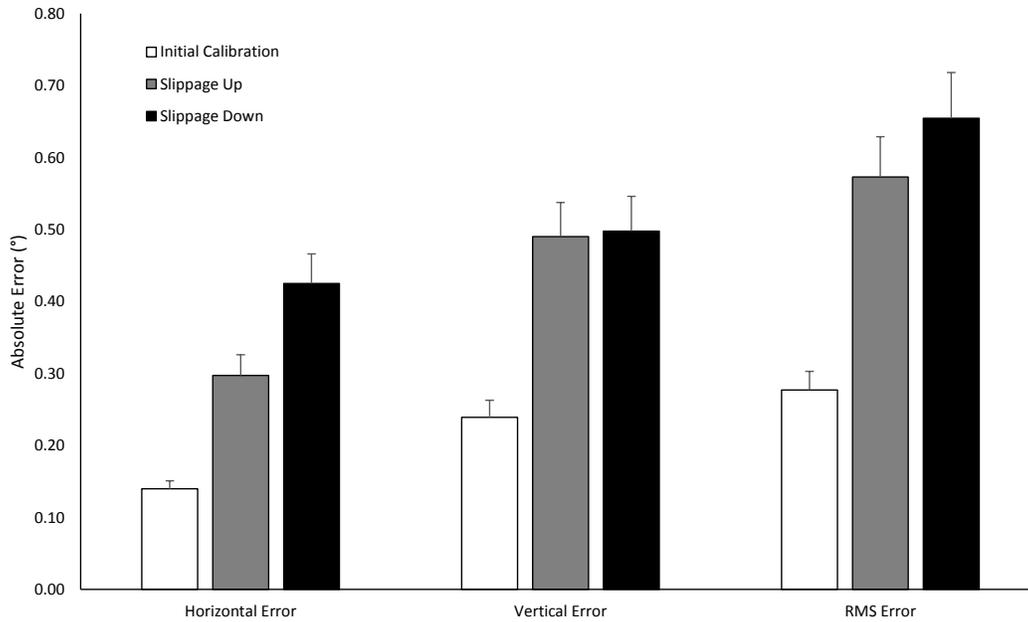

Figure 6. Absolute gaze error (horizontal, vertical and RMS; *M* and *SE*) after initial calibration as well as after slippage of the goggles (Up vs. Down) and application of the proposed *slippage vector* recalibration algorithm in Experiment 3.
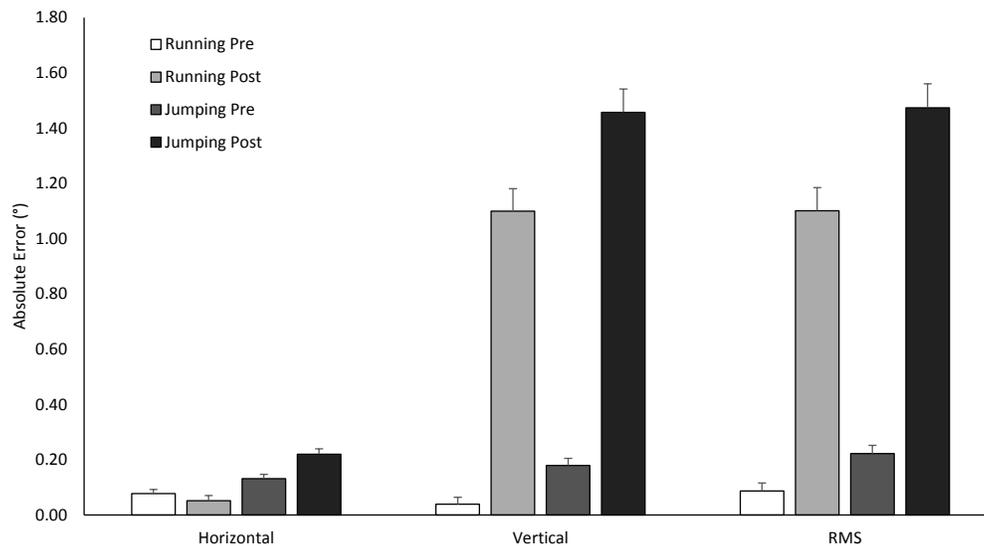

Figure 7. Absolute gaze error (horizontal, vertical and RMS; *M* and *SE*) as a function of movement type (Running vs. Jumping) and of measurement (Pre vs. Post) in Experiment 4.

This increase was mainly caused by the vertical error ($M = 1.17°$, $SE = 0.04°$). By separating the two tasks, it seems that movements with higher peak accelerations (jumping) caused higher slippage angles and, therefore, larger errors in gaze estimation than smoother movements (running). However, the achieved average estimation accuracy of $1.28°$ ($SE = 0.09°$) confirmed the applicability of the system in dynamic situations – and this even without applying the previously analyzed *slippage vector* recalibration method (which would reduce the errors even further).

In sum, it can be stated that the validation tests confirmed the applicability of the implemented eye-tracking system for static as well as dynamic lab tasks. With accuracies of $0.28°$ RMS error in static and $1.28°$ (uncorrected) RMS error after dynamic movements the system was well within reported accuracy ranges for commercial mobile eye trackers, especially as the providers of commercial systems are usually reporting static accuracy only. On top, the implemented slippage vector recalibration procedure was proven to significantly reduce errors caused by slippage of the goggles relative to the head (from up to uncorrected $25°$ reduced to $0.62°$ RMS error on average).

Application Scenarios

The implemented and validated system can be applied in a variety of scenarios. As the complexity of the gaze-assignment process may significantly differ over these scenarios, in the following, two use cases will be presented with an either poorer or richer assignment procedure. After a short introduction into the particular field of research, special attention will be directed towards the methods of analysis. The first use case is targeted more towards basic and the second one more towards applied research.

Scenario 1: Basic Research on Quiet-Eye Mechanisms

Originally found in applied sport settings, a gaze strategy called the "quiet eye" (QE) has become a "hot topic" over the last years in sport science research. The QE is defined as the final fixation or tracking gaze before movement initiation (Vickers, 1996). Since the search for functional mechanisms behind this phenomenon constitutes a main research question of our group, an experimental paradigm was developed that allows for independent manipulations of the QE duration in order to address certain characteristics that might explain its functionality for motor performance and learning (cf. Klostermann, Kredel, & Hossner, 2013, 2014). Typically, this is done in a precision task in which retro-reflective balls must be thrown as precisely as possible at targets that are presented on a large screen (see Figure 8). Since participants execute the throwing movement in accordance to an external pacing rhythm, the onset of the QE can be manipulated by presenting the target either earlier or later with respect to movement initiation.

Emphasizing research methodology, we used the integrated gaze analysis system described above to automatically evaluate the gaze data gathered during the experimental trials. By tracking not only the head pose, but additionally the hand and ball position in space and synchronizing the data recording with stimulus onsets on the screen, we were able to

automatically identify not only the moment of the movement initiation, ball release and impact, but also the onset, offset and the location of the QE (applying a dispersion-based fixation detection algorithm introduced by Nyström & Holmqvist, 2010). The completely automated process enabled us to conduct 12 QE-related experiments with on average 22 participants and 200 trials over the last 3 years with minimal manpower, i.e., with only one person involved in the analysis phase.
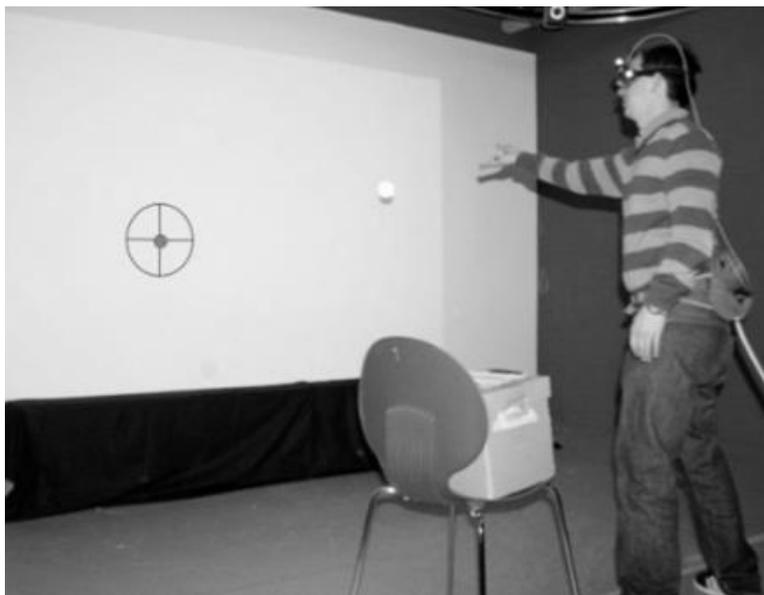

Figure 8. Experimental paradigm for QE research. The participant is wearing the integrated eye tracker and performs an underhand throw with a retro-reflective ball at a target presented at the life-sized screen.

A further basic research direction within our group aims towards the exploration of the functionality of peripheral vision, in particular, how gaze anchoring can help to track multiple objects simultaneously. Beyond the application of the integrated gaze analysis system, in this setting, the introduced vector-based approach can easily be extended towards a mapping of different stimulus locations to foveal, para- and perifoveal conical areas around the central gaze vector so that the gaze analysis is enriched by taking the peripheral information distribution into account. First results within this research direction are described by Vater, Kredel and Hossner (2015).

Scenario 2: Applied Research on Gaze Strategies in Volleyball Defense

In more applied research settings, the gaze analysis system typically has to cope with more dynamic behavior of the participants. This was particularly true in investigations on decision making and gaze strategies in beach-volleyball defensive actions. In the respective experiment (Hossner, Klostermann, Kredel, Schläppi-Lienhard, & Vater, 2015), 16 female and 16 male Swiss Elite players as well as 16 female and 16 male Swiss Near-elite players were subjected to 12 videos with 20 attacking scenes each (10 diagonal smashes, 5 cut shots,

5 line shots in randomized order). The scenes were presented from the perspective of a defense player on a large projection screen. In half of the videos participants were required to react as they would do on the field (action condition), whereas the other half of the videos was temporally occluded (occlusions: -40 ms, -120 ms, -200 ms, -280 ms before ball-hand contact) and participants had to name the attack variant (occlusion condition). Under both conditions, decision accuracy as well as gaze was recorded. Further, in the action condition, movement initiation time was calculated on the basis of participants' body kinematics by using the Vicon motion-capture system.

During data acquisition, the experimenter manually controlled the gaze accuracy after each block of 20 trials. If the accuracy was within the acceptable range (smaller than 2° average RMS error), the next block was started, if not, the eye tracker calibration was repeated. As participants moved very dynamically in the action condition, special attention had to be directed towards the recalibration procedure between trials in order to assure accurate and reliable gaze data. As a consequence, the above described basic *slippage vector* recalibration procedure was refined in such a way, that not only the current trial's fixation distance to the fixation dot was taken into account, but a *slippage function* was estimated over consecutive trials and used for an offline correction of the gaze vector. In general, it can be stated that this approach increased the recalibration quality and its stability against noise significantly as fixation position outliers were eliminated by repeated measures for the *slippage function* estimation.
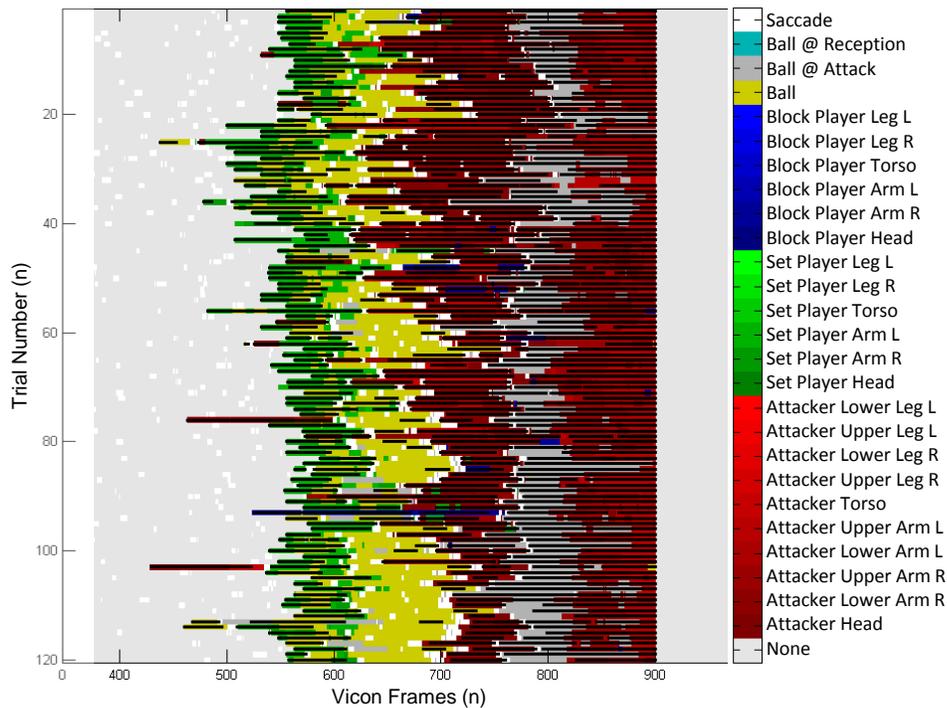

Figure 9. *Gaze Assignment Plot* (GAP) as a novel visualization solution for gaze data of a single participant. Gaze patterns of different trials (vertical axis) are displayed over time (horizontal axis), while the thin black lines represent fixations (spatially static gaze within 1° area). White spaces represent saccades and colors indicate mappings of the gaze vector to different cue regions.

During data collection, each participant was subjected to approx. 90 minutes video material of attacking scenes. Taking this immense amount of data points into account (220 gaze samples per second), a further challenge was the development of a feasible visualization for the descriptive analysis of the captured gaze data. To this regard, *Gaze Assignment Plots* were introduced (GAP, see Figure 9). In each row of the plot, the gaze pattern of one experimental trial is displayed over time. The trials can be aligned with common events, e.g., with the ball-hand contact of the attacker (corresponding to frame 900 in Figure 9). The assignment of the foveated cue region was automated by calculating the Euclidean distance between the gaze vector position and each stimulus position on the screen for each time step and selecting the cue with minimal distance to the gaze vector.

In the GAP, the color represents the mapping to these different cue regions in such a way that white colored areas represent saccadic eye movements, light gray areas are gaze positions outside the screen and the other colors map relevant body segments of the opponents or the ball position on the basis of a nearest-neighbor approach (for details, see legend on the right of Figure 9).

As additional information, thin black lines over the colored gaze patterns represent fixations, which are defined as spatially static gaze within 1° area for longer than 100ms. For the automated identification of the fixations, we use a dispersion-based algorithm and for the saccadic eye movements an adaptive threshold velocity-based algorithm (Nyström and Holmqvist, 2010). After having all (in Figure 9: 120) trials temporally aligned to each other, individual gaze variables can be aggregated automatically and, in turn, subjected to further statistical analyses.

Conclusion and Outlook

After having identified the main limitations of the current state-of-the-art in mobile gaze analysis hindering the broader use of eye-tracking, our aim was to overcome these limitations by using light-weight and non-obstructive eye-tracking equipment with high temporal and spatial resolution and by applying a vector-based gaze analysis procedure with regular automated checks between data collection trials, an automated recalibration procedure and an objective data-to-stimulus assignment process. Within this chapter, the design of the system was described, its functionality and accuracy was evaluated in static and dynamic settings and it applicability was illustrated by two representative use cases. The validated system proved its feasibility to analyze larger amounts of data in mobile settings while keeping accuracy levels high. As the markedly subjective fixation and saccade detection and stimulus assignment processes in video-based mobile eye-tracking have been eliminated, the objectivity of the analysis process was significantly increased and the time effort for analysis could be reduced considerably. On this basis, the introduced system allows to aggregate gaze behavior of larger samples sizes in mobile settings, hereby significantly improving the reliability for generalization.

Even if the accuracy of the system in dynamic situations is already comparable to commercial mobile eye-tracking systems, the proposed *slippage vector* recalibration procedure can further reduce the remaining errors and increase accuracy and reliability of the system. However, as this procedure uses fixation dots in between-trial intervals, the reliability

of the procedure is heavily depending on the attention paid by the participants. That is why we currently enhance this procedure towards an online estimation of a *slippage function* over consecutive trials. Another limitation is the current offline implementation of the analysis process rather than a direct online correction and data-to-stimulus assignment. As this online feature is mandatory for gaze feedback, e.g., in gaze training interventions, a further current development focuses on the implementation of online filters and on the reduction of computing time for the gaze estimation and analysis routines. Additionally, it is obvious that the postulated similarity of the test to the real situation might be reduced by the fact that participants are enforced to perform in a lab setting due to the tracking requirements of the head or camera pose. However, as motion tracking systems are becoming more and more flexible and usable in unrestricted spaces (e.g., using local positioning systems or fused 9DOF-IMU sensors), in the near future, the proposed vector-based approach seems to become applicable even outside the lab under on-field or even under competition conditions.

To conclude, we think that our proposed vector-based gaze estimation and analysis procedure enables researchers within the field of perception-action diagnostics to reliably estimate gaze patterns in static as well as dynamic settings with minimal manpower required for data collection and, in particular, for data analysis. Thus, the procedure might offer a useful approach for further disentanglement of crucial mechanisms in perception-action research.

References

Duchowsky, A.T. (2003). *Eyetracking methodology, theory and practice*. London: Springer.

Evans, K.M., Jacobs, R.A., Tarduno, J.A., & Pelz, J.B. (2012). Collecting and analyzing mobile eye-tracking data in outdoor environments, *Journal of Eye Movement Research*, *5*, 1-19.

Farrow, D., & Abernethy, B. (2007). Wahrnehmung von Expertinnen und Experten im Sport: Einige Kernfragen und -probleme [Expert perception in sports: Some key questions and problems]. In N. Hagemann, M. Tietjens, & B. Strauß (Eds.), *Psychologie der sportlichen Höchstleistung* (pp. 71-92). Göttingen, Germany: Hogrefe.

Haslwanter, T. (1995). Mathematics of three-dimensional eye rotations, *Vision Research*, *35*, 1727-1739.

Hossner, E.-J., Klostermann, A., Kredel, R., Schläppi-Lienhard, O., & Vater, C. (2015). *Decision making and gaze strategies in beach volleyball defense: On expertise and the maximization of information*. Manuscript in preparation.

Klostermann, A., Kredel, R., & Hossner, E.-J. (2013). The "Quiet Eye" and motor performance: Task demands matter! *Journal of Experimental Psychology: Human Perception & Performance*, *39*, 1270-1278.

Klostermann, A., Kredel, R., & Hossner, E.-J. (2014). The quiet eye without a target: The primacy of visual information processing. *Journal of Experimental Psychology: Human Perception & Performance*, *40*, 2167-2178.

Kohlbecher, S., Bartl, K., Bardins, S., & Schneider, E. (2010). Low-latency combined eye and head tracking system for teleoperating a robotic head in real-time. In C. H. Morimoto, I. Istance, A. Hyrskykari, & Q. Ji (Eds.): *Proceedings of the 2010*

Symposium on Eye-Tracking Research and Applications (ETRA '10) (pp. 117-120). New York: ACM.

Kredel, R., Lienhard, O., Klostermann, A., Koedijker, J., Michel, K., & Hossner, E.-J. (2011). Perceptual skill identification in a complex sport setting, *BIO Web of Conferences*, *1*, 51.

Kumar, N., Kohlbecher, S., & Schneider, E. (2009). A novel approach to video-based pupil tracking. Paper presented at the IEEE International Conference on Systems, Man and Cybernetics 2009. Retrieved September 4, 2014, from IEEE Xplore.

Mann, D.L., Abernethy, B., & Farrow, D. (2010). Action specificity increases anticipatory performance and the expert advantage in natural interceptive tasks. *Acta Psychologica*, *135*, 17-23.

Mann, D.T.Y., Williams, A.M., Ward, P., & Janelle, C.M. (2007). Perceptual-cognitive expertise in sport: A meta-analysis. *Journal of Sport and Exercise Psychology*, *29*, 457-478.

Nyström, M., & Holmqvist, K. (2010). An adaptive algorithm for fixation, saccade, glissade detection in eye-tracking data. *Behavior Research Methods*, *42*, 188-204.Roth, H.L., Lora, A.N., & Heilman, K.M. (2002). Effects of monocolar viewing and eye dominance on spatial attention. *Brain*, *125*, 2023-2035.

Schneider, E., Villgrattner, T., Vockeroth, J., Bartl, K. Kohlbecher, S., Bardins, S., Ulbrich, H., & Brandt, T. (2009). EyeSeeCam: An eye movement-Ddiven head camera for the examination of natural visual exploration. *Annals of the New York Academy of Sciences*, *1164*, 461-467.

Vater, C., Kredel, R., & Hossner, E.J. (2015). *Detecting single-target changes in multiple object tracking: The case of peripheral vision*. Manuscript in preparation.

Vickers, J.N. (1996). Visual control when aiming at a far target. *Journal of Experimental Psychology: Human Perception & Performance*, *22*, 342-354.

Williams, A.M., Davids, K., & Williams, J.G. (1999). *Visual perception and action in sport*. London: Taylor & Francis.