Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 176 (2020) 2020–2029

Procedia Computer Science

www.elsevier.com/locate/procedia

24th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems

Towards expert gaze modeling and recognition of a user's attention in realtime

Nora Castner[a,b,*], Lea Geßler[b], David Geisler[a,b], Fabian Hüttig[c], Enkelejda Kasneci[a,b]

[a] Human-Computer Interaction, University of Tübingen, Germany
[b] Institute of Computer Science, University of Tübingen, Germany
[c] Department of Prosthodontics, University Hospital Tübingen, Germany

Abstract

One of the appealing areas of expertise research is devoted to measuring the effectiveness of training programs for novices. With recent progress in eye tracking, gaze-based interaction systems recognize a user's attention and can direct it accordingly. Moreover, dynamic visualization of an expert gaze model facilitates novice training by guiding the gaze to relevant areas. In addition, the system should be aware of realtime attention to remove an overlay that could occlude relevant information. We use an implementation of subtle gaze direction (SGD) and the simplified scanpath of a dentist to train naive participants in finding anomalies in dental radiographs. We were able to effectively direct user gaze to relevant image features without occluding the area when attention was recognized. Additionally, participants reported that the intervention was helpful for image inspection. The results of the model intervention show minimal improvements in anomaly detection, which is expected of naive subjects. We advocate that the system has the potential to be highly effective for advanced students and trainees with a certain foundation of conceptual knowledge.

Keywords: Eye Tracking; Gaze-based Interaction; Attention Guiding; Expertise; Learning

1. Introduction

Pervasive eye tracking provides a rich source of input to systems regarding a user's attention [6, 43]. As the interpretation of attention is often open to debate, we restrict the current work's definition to the visual attention aspect, as measured by the gaze locations over time for a given stimuli. Thus, gaze aware systems can detect user attention to certain areas at a given time and give customized support for the current task in a way that exploits natural human behavior, e.g. scanning a scene [29, 45]. One area that has shown promising applicability of these systems is intelligent tutoring systems. They cater to the user by offering adaptability and personalized feedback.

* Corresponding author. Tel.: +49-(0)7071-29-70492.
E-mail address: nora.castner@uni-tuebingen.de

10.1016/j.procs.2020.09.238

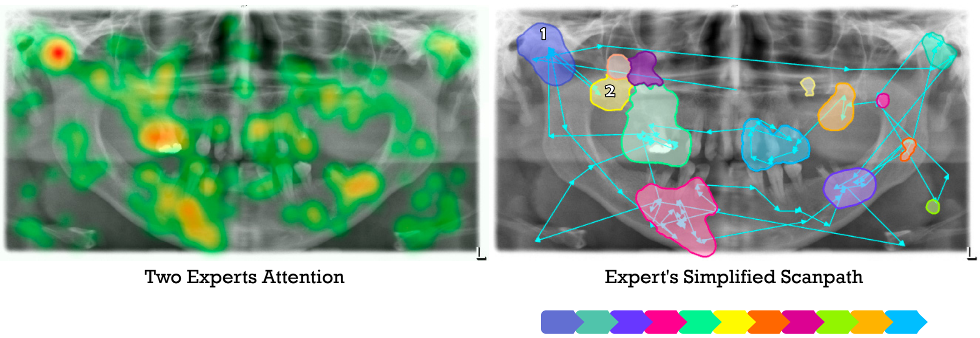


Fig. 1: Gaze guiding through experts' attention. AOIs are calculated from the heatmap. Then, the simplified transitional behavior becomes the order of presentation.

Using students' realtime gaze behavior to register attentional information has shown to successfully serve as input to adapt training systems in online learning portals [44, 40, 3, 7]. More important, they can augment traditional teaching approaches for effective visual inspection, by better breaking down complex imagery based on the realtime attentional information [41, 31]. One field that can highly benefit from gaze-aware tutoring is medical image inspection.

Medical experts are accountable for a high degree of sensitivity and specificity in diagnoses, since proper patient care is at stake. Visual search strategies can exemplify their perceptual expertise, where successful verification can rely on the slightest changes in the image features [39, 26, 20, 25, 47, 21]. In diagnostic radiology, experts initially perceive abnormalities faster and can also better discriminate what is irrelevant and what can indicate a pathology compared to novices [26, 22, 48].

Training perceptual expertise in radiology is a key component in novice training. For radiograph images, directed training in high volume has shown increased perceptual sensitivity in low-contrast target recognition [46] and semantic target recognition [11]. However, this approach becomes comparable to traditional massed practice approaches that require time and numerous images. Research has drawn attention to using gaze models for students or trainees [31, 30, 17, 16] to improve their perception to relevant features and thus streamline the learning process. Though proficient performance can be obtained, it has also been stressed that conceptual knowledge accelerates proper diagnostic interpretation [19, 12, 30].

Our work combines domains that have been previously running in parallel: Expert gaze modelling for learning and user-attention awareness. We designed a framework for gaze guiding based on expert viewing behavior on dental radiographs while recognizing a user's real-time gaze. Our interests are two-fold, 1) whether we can effectively guide a user's gaze to relevant regions of an image without occluding any information and 2) whether expert gaze guiding can improve perceptibility of anomaly features for non-experts. We present an exploratory evaluation of the intervention design with naive participants and assess its efficacy by its ability to guide the gaze unobtrusively and from usability feedback. Additionally, we look at detected anomaly features; however, we are aware that diagnostic performance would be more appropriately evaluated with students and advanced trainees, who have a more appropriate skill set for pathology interpretation.

2. Related Work

Gaze-based systems can offer an array of methods to visualize either a user's gaze in realtime or a gaze guiding model. Gaze contingency is visualizing a user's gaze, e.g. spotlighting, unmasking or unblurring, etc. [15, 38, 37]. For example, [28] used a white ring to indicate expert dentists' online gaze while viewing periapical (One tooth/ region of teeth) radiographs. Recognizing areas that were previously attended to and occluding them was shown to reduce workload during target detection [41]. Conversely, [14] found no effect on target detection accuracy or response time in a search task when users could see their own fixated or "yet to be fixated" regions overlayed in a colored translucent grid form. Moreover, they conclude that their protocol assumes a target will be detected if it is

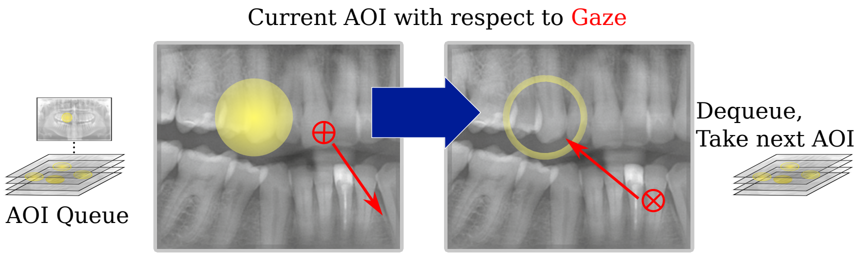


Fig. 2: Illustration of feedback animation. When the gaze attention (red cross-hair) is not directed towards the AOI, it pops up as a semi-translucent yellow circle (left image). When the gaze attention goes towards or is in the AOI, it presents the feedback as a translucent yellow ring (right image).

fixated on; it does not account for errors in target interpretation [14]. Regarding interpretation, tasks involving domain expertise can lead to recognition or decision errors (e.g. false negatives), where novices were more prone to these errors [34, 5, 1]. Concerning novice training, [42] found that blurring novice basketball players' periphery improved their decision making performance and that performance was even stable longitudinally. Specifically in medical image inspection, [35] found that gaze contingent windows on a chest radiograph acted as a guide for foveal vision towards inconspicuous nodules in the periphery, improving time to detection in experts. To our knowledge, gaze contingent feedback in novice medical image inspection has yet to be investigated.

Illustrating an expert's gaze as opaque yellow dots guided students to relevant features of the task [31]. Similarly, blurring areas where experts did not attend guides students' gaze without occluding relevant features [30]. Showing an experts' gaze dynamically as red dots coupled with think-aloud protocols was used for training both novice and experts in radiograph interpretation [19]. However, these aforementioned systems passively display an expert model and lack the user awareness and interaction.

Gaze-guiding systems that adapt to a user's gaze online have also been shown to be effective [38, 18, 41]. However, illustrating the user's gaze or a region of interest in a salient fashion can lead to feature occlusion that could hinder decision making in certain detection tasks. In order to not occlude potentially relevant regions, [2] proposed subtle gaze direction (SGD). It guides gaze during visual search by manipulating either the luminance or color and present it in the subject's periphery. When a saccade is detected towards the area of interest, the masking is removed [2]. Similarly, SGD with flickering in the periphery has been successful in gaze-guiding [49].

We employ a version of the SGD using areas of expert attention when examining panoramic dental radiographs (OPTs). We chose expert attentional areas because efficient anomaly detection is apparent in their search strategies. Among experts, scanpath variability can be high as they tend to employ their own "short cuts" [33, 32, 36] However, it has been found that relativity similar scanpaths can indicate correct medical image interpretation [13]. Therefore, our model is an expert's scanpath with respect to areas of attention of theirself and another highly similar expert scanpath. We present our SGD implementation with this expert model to non-experts.

3. Methods

Participants. We recruited 27 (20 male, $M_{age} = 28.4$) participants. Their backgrounds were mainly computer science (13). However, one was a medical assistant and another was a paleo-anthropologist. Both had more experience with general human anatomy and some radiology, though not specifically dentistry. 11 participants wore glasses during the experiment.

Experimental Paradigm. Prior to the experiment, all participants were debriefed regarding eye-tracking and the general protocol and signed a consent form. At the end, they were asked to fill out a brief questionnaire regarding the task difficulty, the gaze feedback, usability etc.

A five-point calibration with four point validation was performed for each subject at the beginning and in the middle of the experiment after a short pause. We followed the same experimental paradigm that can be found in [8]. Participants saw ten panoramic dental radiographs (OPTs). Each OPT was presented twice subsequently: First for

90 seconds, where they were instructed to inspect the image and then again where they could mark any areas they perceived as an anomaly. For each participant, we randomly determined which five OPTs would show the gaze-guiding; the other OPTs provided no feedback. This way we could compare within-subjects, whether the feedback had an effect. The second presentation of the OPTs had unlimited time for participants to mark detected anomalies at their own pace. A chin rest was used to assure stable gaze signal.

Expert Ground Truths. The OPTs were taken from Castner et al. [9, 8] and had pre-determined ground-truth anomaly information from two dentists involved in the project. The ground truth data was used to calculate the anomaly detection performance of the current participants. An anomaly was labeled as detected (true positive) if the participant marked the respective area of a ground truth anomaly. False negatives and false positives were if the participant did not mark a specific ground truth anomaly area or marked an area where no anomaly was present, respectively (see Castner et al. [9] for further details on the detection performance protocol).

To create the areas of interest (AOIs), we chose gaze data from two experts from a previous data collection with expert OPT inspection. Experts from this data collection had an average of 10 years of experience. Through similarity clustering, two experts were found to have scanpaths highly similar to all other experts' scanpath (see [10] for further details); their data was chosen to develop the expert model. From their heatmap, areas with higher concentration of gaze are segmented as illustrated in the right image in figure 1. We chose the scanpath of the more accurate (higher detected anomalies) of the two experts to provide transitional behavior. We preferred a simplified version of the transition, denoting the first glance into an AOI and not revisits, since it was determined that revisits would be too hard to follow. An example of a simplified scanpath is also found in figure 1: The first blue AOI is looked at (1) then transitions to four other AOIs were made before going back to the first AOI, we omit the revisit and set the next transition to the yellow AOI (2). Without revisits, scanpaths ranged from 9 to 23 transitions, and with revisits, they ranged from 88 to 175 transitions.

Software. We based the experiment software off the experiment designer and gaze-contingent feedback developed in [38]. This software already has the usability for presenting image stimuli for either a set time or key-press interrupt. We added an on-screen drawing tool, so we could gather the anomaly detection recall and precision of the non-experts. We also added the ability to upload customized feedbacks with AOI positions as csv-files.

We incorporated the AOIs and the ability to recognize attention towards them; Our method is based on the subtle gaze direction (SGD) method from [2]. We added a short delay of 5 seconds, before the first AOI pops up, so participants could scan the image shortly.

AOIs for a certain feedback are placed into a queue. Upon an animation timer timeout, the current AOI is dequed and painted over the stimulus. For this work, we set the timer to timeout every 3.8 seconds so participants would not feel rushed, as they were non-experts. The AOI is initially illustrated as yellow (RGB : 252, 252, 103) with a translucent radial gradient (left image in figure 2). We chose this color as we felt it would be salient against our grayscale stimuli.

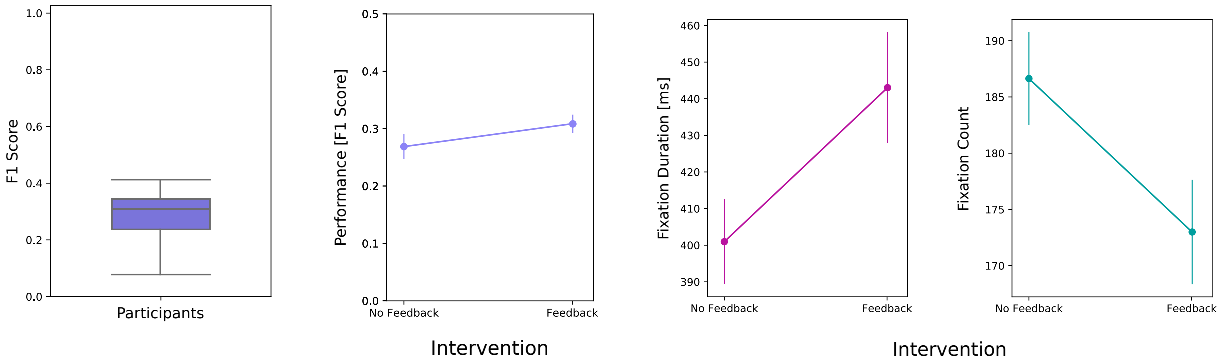
In order to avoid occlusion of important image features, we repaint the AOI area with a translucent yellow ring (right image in figure 2), when our SGD implementation detects the gaze angle as going towards the AOI. Where the angle, α, is calculated as follows:

$$\alpha = \cos^{-1}\left(\frac{\vec{v} \cdot \vec{t}}{|\vec{v}| \cdot |\vec{t}|}\right), \tag{1}$$

where $\vec{v}$ indicates the vector from the previous gaze point to the current gaze point and $\vec{t}$ indicates the vector from the previous gaze point to the target AOI. We calculate α five times using equation 1: with one $\vec{t}$ to center coordinates of the AOI and then $\vec{t}$ for each of the corner coordinates of its bounding box. We calculate the previous gaze as the average of the last two gaze coordinates stored in a buffer. We take the minimum of the five angles and subtract it from 360° if it is larger than 180°.

Then, if α is between 0 and 10°, the AOI updates from the circle to the ring. This threshold was used in [2], and was determined stable when testing our implementation. For gaze input, we used the SMI RED250 remote eye tracker running at 60Hz.

4. Results



(a) Non-Expert Performance (b) Performance with Intervention (c) Gaze Behavior with Intervention

Fig. 3: Performance as measured by the F1 Score (a) overall images (b) comparing the intervention of expert gaze feedback against no feedback, and (c) the gaze behavior with respect to feedback or no feedback. Means (circles) and standard errors (tails) are plotted for all figures.

Performance and Gaze. We calculated the sensitivity and precision of the participants over all images, then calculated the harmonic mean (F1 score) between the metrics. Sensitivity is the true positive rate (TPR), precision is the positive predictive value (PPV). The F1 score is $2 \cdot (PPV \cdot TPR/PPV + TPR)$. One participant's performance was omitted upon learning that they did not understand the instructions given at the beginning. As was expected with non experts, performance in OPT anomaly detection was relatively low: The average F1 score overall was M $=$ 28.42%, SD $=$ 8.45. The distribution is shown in figure 3a.

To see if there were any effects of the expert gaze feedback intervention, we ran a repeated measures t-test on both the performance and the gaze behavior for "feedback" versus "no feedback" conditions. No major effect was found for the intervention on performance ($t(26) = -2.021, p = 0.054$), with the performance with the feedback was slightly better (M $=$ 30.80%, SD $=$ 8.23) than without the feedback (M $=$ 26.85%, SD $=$ 10.97.). Figure 3b shows the performance with respect to the intervention.

However, the intervention had a stronger effect on the gaze behavior. Average fixation durations were higher for the feedback condition (M $=$ 443.03, SD $=$ 78.76) compared to the no feedback condition (M $= 400.96ms$, SD $=$ 60.29, $t(26) = -4.704, p < 0.0001$). Additionally, the average fixation count for the feedback condition was lower (M $=$ 173.0, SD $=$ 24.15) than the no feedback condition (M $=$ 186.64, SD $=$ 21.41, $t(26) = 4.502, p = 0.00012$).

Attention to AOIs. To assess whether the intervention successfully guided the gaze behavior, we looked at subjects' gaze behavior in relation to the AOIs as shown in figure 4. We ran repeated measures t-test for AOI glances and transition similarity.

We looked at the effect of the intervention on the AOI glances. We measure AOI glances as the proportion of a glance on an AOI in relation to the total AOIs from the expert model. We found that with the feedback, subjects had significantly higher proportion of glances (M $=$ 0.8359, SD $=$ 0.0935) than without the feedback (M $=$ 0.7060, SD $=$ 0.0863, $t(26) = -8.165, p < 0.0001$).

We looked at the effect of the intervention on the similarity of subject's AOI transitions to the expert's transition. Similarity was calculated with the levenshtein distance [24] for subjects' scanpaths compared to the expert's scanpath and normalized to the length of the longest scanpath. We found that with the feedback, subjects had significantly more similarity to the expert (M $=$ 0.7203, SD $=$ 0.072) than without the feedback (M $=$ 0.7937, SD $=$ 0.0416,

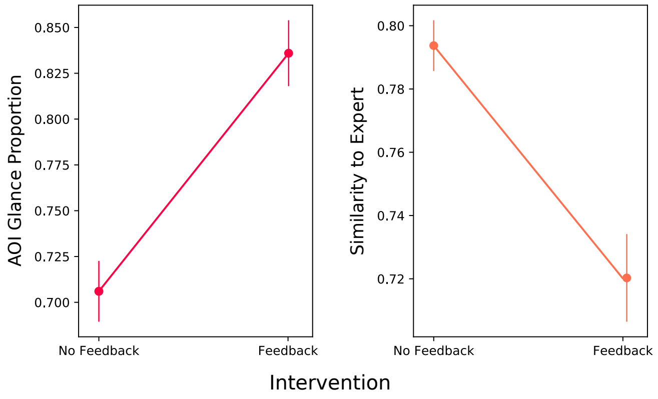


Fig. 4: Performance as measured by the F1 Score for each image with respect to intervention.

$t(26) = 4.791, p < 0.0001$). Figure 5 shows the transitional information for one image of subjects with (middle) and without (right) the intervention compared to the expert's gaze transitions relative to the AOIs (Left). Here, it is evident that the similarity is of the subjects who received the gaze feedback is closer to the expert's gaze behavior than the subjects who received no feedback: Note the transitions to (lines originating) and from (lines landing) AOI 5 (burgundy).

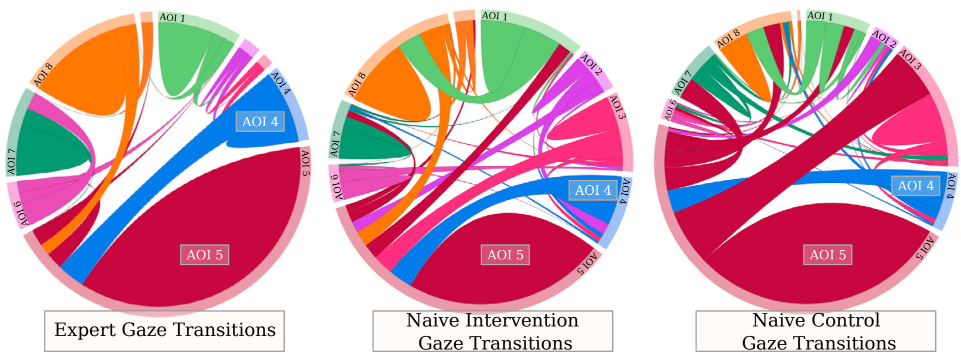


Fig. 5: Example of AOI transitions for one image. Where the left most diagram is the expert's transitional information and the middle is the transitional information of subjects who received the gaze intervention and the right most is the transitional information of subjects who received no gaze intervention .

User response. Regarding usability, we asked subjects to fill out a short questionnaire about the task and the gaze feedback. Average responses for the questions are plotted in figure 6. Overall, the subjects found the task difficult and were not confident in their performance. This could be expected as the nature of anomalies in these images are likely to be very subtle to the untrained eye. Moreover, they were overall positive regarding the intervention, finding it beneficial and depending on it to complete the task. Some participants made informal comments to the researchers that, after a few images with interventions, they started to recognize features (e.g. dark shadows in the gums), which they felt could be indicative of something abnormal (peridontitis). They did however find the task a bit too long and slightly rushed. These responses will be helpful for future testing and system development.

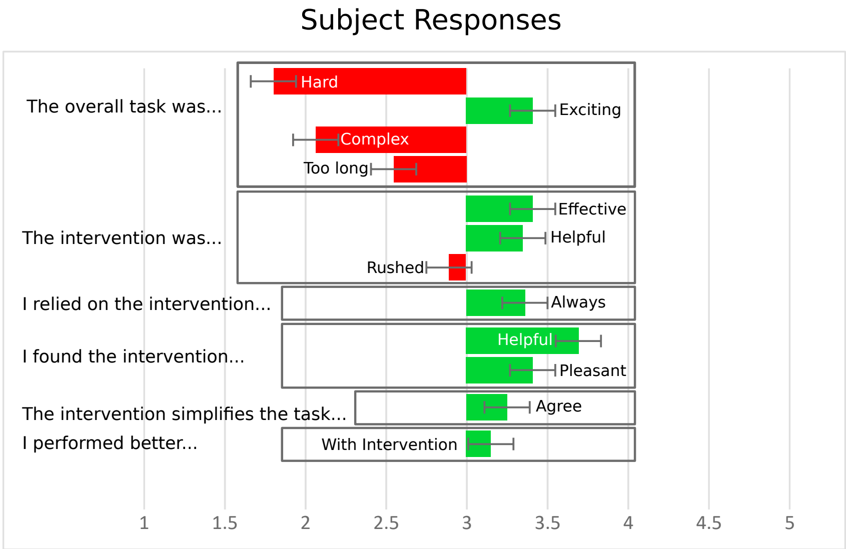


Fig. 6: Average responses for questionnaire regarding the task and the gaze intervention. The task was reported as difficult for the non-experts. They did report that the feedback was helpful and they used it.

5. Discussion

Overall, there were significant differences in the gaze behavior. When presented with the expert gaze model, participants exhibited fewer fixations, but longer fixation durations. This behavior could be indicative of more information processing and associated with novices [20, 32, 33, 27]. Additionally, the gaze model elicited a higher proportion of AOI glances. Therefore, there was more attention to relevant-areas of the image. However, subjects did not detect anomalies in dental radiographs with high accuracy. The expert gaze model intervention did not significantly improve performance compared to no intervention at all. One reason for this finding could be the low sample size. Additionally, this low sample size could explain the high variance in the gaze behavior for both the intervention and no intervention condition. Further research with an appropriate sample size to observe a significant difference is necessary.

Moreover, participants reported feeling more confident with the gaze intervention and relied on it to complete the task. They successfully followed the expert gaze model and were more similar to the expert's AOI transitional behavior. Although, they lacked the conceptual knowledge that facilitates the proper interpretation of the relevant features. Previous research has also indicated that search pattern training draws attention to relevant areas, but did not affect performance [33, 19, 23]. Waite et al. [48] highlights the reciprocity of perception and cognition in diagnostic performance: For instance, initial feature localization, then conceptual knowledge facilities the decision that this feature needs further inspection (e.g. difference in contrast, and area prone to anomalies, etc.) and whether it is recognized as a specific pathology or could be ruled out.

It should be noted that dental radiographs, as with all medical images, are highly complex in nature and require some form of conceptual knowledge to interpret reliably. Presenting only ten OPTs may not have been enough for a significant training effect. Considering the low number of OPTs, the naive participants seemed to recognize features the intervention highlights in later images as they reported. To get improved performance in naive observers, [11] used around 800 images to improve hip fracture detection. Further research is needed that addresses the optimal amount of images needed to improve interpretation, without inducing fatigue while still providing ample time to interact with the gaze model. In our study, we were limited to investigating short term effects of training naive participants. A longitudinal study regarding the gaze-aware feedback system on naive subjects' or novices' learning overtime would be an interesting aspect for further research. Furthermore, the notion of implicit feature learning is also interesting for future work. Beesley and colleagues [4] found gaze contingency aided in implicit rule learning. Staggering training sets of certain types of anomalies and expert gaze behavior related to them may improve detecting the features indicative of these anomalies.

Moreover, we show a potentially effective learning intervention for either novices or more advanced dentists. Students undergo intense studying and exposure to get to the level of professional expertise that makes them successful later in their careers. More effective learning interventions can smooth the transition of students to residency and professional environments by minimizing the knowledge gap between each stage. With better preparation, less professional resources need to be expended on supervising incoming residents and early professionals. Even then, *expert* is never a final state, but should always be open for further learning and improving. Generally, it has been found that experts and more advanced trainees benefit highly from gaze interventions [19, 21]. Our implementation of the SGD with expert AOIs could also potentially be catered to advanced learners, in hopes to further fine-tune established skills.

6. Conclusion

We employ subtle gaze direction to present expert attention while examining panoramic dental radiographs. Our method does not occlude relevant areas in the foveal vison, as it recognizes when attention is directed towards the area. We could successfully guide the gaze to relevant image features and promoted further inspection. Our findings with naive participants showed that the gaze feedback could not develop successful dental radiograph diagnosis, but elicited gaze transitions similar to the expert model. They also felt more confident and that the framework helped them properly inspect radiographs. This aspect suggests further research to promote SGD as a suitable way to illustrate expert gaze behavior in learning interventions with students or advanced trainees.

Acknowledgements

Dr. med. Dr. med. dent. Constanze Keutel from the Department of Radiology, Center of Dentistry, Oral Medicine and Maxillofacial Surgery at the University Hospital Tübingen for their expertise and help overseeing the project with Dr. Hüttig.

References

[1] Baghdady, M.T., Carnahan, H., Lam, E.W., Woods, N.N., 2014. Dental and dental hygiene students' diagnostic accuracy in oral radiology: effect of diagnostic strategy and instructional method. Journal of dental education 78, 1279–1285.

[2] Bailey, R., McNamara, A., Sudarsanam, N., Grimm, C., 2009. Subtle gaze direction. ACM Transactions on Graphics (TOG) 28, 1–14.

[3] Barrios, V.M.G., Gütl, C., Preis, A.M., Andrews, K., Pivec, M., Mödritscher, F., Trummer, C., 2004. Adele: A framework for adaptive e-learning through eye tracking. Proceedings of IKNOW , 609–616.

[4] Beesley, T., Pearson, D., Le Pelley, M., 2015. Implicit learning of gaze-contingent events. Psychonomic bulletin & review 22, 800–807.

[5] Bruno, M.A., Walker, E.A., Abujudeh, H.H., 2015. Understanding and confronting our mistakes: the epidemiology of error in radiology and strategies for error reduction. Radiographics 35, 1668–1676.

[6] Bulling, A., 2016. Pervasive attentive user interfaces. Computer , 94–98.

[7] Calvi, C., Porta, M., Sacchi, D., 2008. e5learning, an e-learning environment based on eye tracking, in: 2008 Eighth IEEE International Conference on Advanced Learning Technologies, IEEE. pp. 376–380.

[8] Castner, N., Kasneci, E., Kübler, T., Scheiter, K., Richter, J., Eder, T., Hüttig, F., Keutel, C., 2018a. Scanpath comparison in medical image reading skills of dental students: distinguishing stages of expertise development, in: Proceedings of the 2018 ACM Symposium on Eye Tracking Research & Applications, ACM. p. 39.

[9] Castner, N., Klepper, S., Kopnarski, L., Hüttig, F., Keutel, C., Scheiter, K., Richter, J., Eder, T., Kasneci, E., 2018b. Overlooking: the nature of gaze behavior and anomaly detection in expert dentists, in: Proceedings of the Workshop on Modeling Cognitive Processes from Multimodal Data, ACM. p. 8.

[10] Castner, N., Kübler, T.C., Scheiter, K., Richter, J., Eder, T., Hüttig, F., Keutel, C., Kasneci, E., 2020. Deep semantic gaze embedding and scanpath comparison for expertise classification during opt viewing, in: Eye Tracking Research and Applications, ACM.

[11] Chen, W., HolcDorf, D., McCusker, M.W., Gaillard, F., Howe, P.D., 2017. Perceptual training to improve hip fracture identification in conventional radiographs. PloS one 12.

[12] Coderre, S., Mandin, H., Harasym, P.H., Fick, G.H., 2003. Diagnostic reasoning strategies and diagnostic success. Medical education 37, 695–703.

[13] Davies, A., Brown, G., Vigo, M., Harper, S., Horseman, L., Splendiani, B., Hill, E., Jay, C., 2016. Exploring the relationship between eye movements and electrocardiogram interpretation accuracy. Scientific reports 6, 38227.

[14] Drew, T., Williams, L.H., 2017. Simple eye-movement feedback during visual search is not helpful. Cognitive Research: Principles and Implications 2, 1–8.

[15] Duchowski, A.T., Cournia, N., Murphy, H., 2004. Gaze-contingent displays: A review. CyberPsychology & Behavior 7, 621–634.

[16] Eder, T.F., Richter, J., Scheiter, K., Keutel, C., Castner, N., Kasneci, E., Huettig, F., 2020. How to support dental students in reading radiographs: effects of a gaze-based compare-and-contrast intervention. Advances in Health Sciences Education: Theory and Practice .

[17] Fichtel, E., Lau, N., Park, J., Parker, S.H., Ponnala, S., Fitzgibbons, S., Safford, S.D., 2019. Eye tracking in surgical education: gaze-based dynamic area of interest can discriminate adverse events and expertise. Surgical endoscopy 33, 2249–2256.

[18] Foulsham, T., Underwood, G., 2011. If visual saliency predicts search, then why? evidence from normal and gaze-contingent search tasks in natural scenes. Cognitive Computation 3, 48–63.

[19] Gegenfurtner, A., Lehtinen, E., Jarodzka, H., Säljö, R., 2017. Effects of eye movement modeling examples on adaptive expertise in medical image diagnosis. Computers & Education 113, 212–225.

[20] Gegenfurtner, A., Lehtinen, E., Säljö, R., 2011. Expertise differences in the comprehension of visualizations: A meta-analysis of eye-tracking research in professional domains. Educational Psychology Review 23, 523–552.

[21] Van der Gijp, A., Ravesloot, C., Jarodzka, H., van der Schaaf, M., van der Schaaf, I., van Schaik, J.P., Ten Cate, T.J., 2017. How visual search relates to visual diagnostic performance: a narrative systematic review of eye-tracking research in radiology. Advances in Health Sciences Education 22, 765–787.

[22] Van der Gijp, A., Van der Schaaf, M., Van der Schaaf, I., Huige, J., Ravesloot, C., Van Schaik, J., ten Cate, T.J., 2014. Interpretation of radiological images: towards a framework of knowledge and skills. Advances in Health Sciences Education 19, 565–580.

[23] van der Gijp, A., Vincken, K.L., Boscardin, C., Webb, E.M., Ten Cate, O.T.J., Naeger, D.M., 2017. The effect of teaching search strategies on perceptual performance. Academic radiology 24, 762–767.

[24] Goldberg, J.H., Helfman, J.I., 2010. Scanpath clustering and aggregation, in: Proceedings of the 2010 symposium on eye-tracking research & applications, pp. 227–234.

[25] Grünheid, T., Hollevoet, D.A., Miller, J.R., Larson, B.E., 2013. Visual scan behavior of new and experienced clinicians assessing panoramic radiographs. Journal of the World Federation of Orthodontists 2, e3–e7.

[26] Gunderman, R.B., Patel, P., 2019. Perception's crucial role in radiology education. Academic radiology 26, 141–143.

[27] Haider, H., Frensch, P.A., 1999. Eye movement during skill acquisition: More evidence for the information-reduction hypothesis. Journal of Experimental Psychology: Learning, Memory, and Cognition 25, 172.

[28] Hermanson, B.P., Burgdorf, G.C., Hatton, J.F., Speegle, D.M., Woodmansey, K.F., 2018. Visual fixation and scan patterns of dentists viewing dental periapical radiographs: an eye tracking pilot study. Journal of endodontics 44, 722–727.

[29] Jacob, R.J., Karn, K.S., 2003. Eye tracking in human-computer interaction and usability research: Ready to deliver the promises, in: The mind's eye. Elsevier, pp. 573–605.

[30] Jarodzka, H., Balslev, T., Holmqvist, K., Nyström, M., Scheiter, K., Gerjets, P., Eika, B., 2012. Conveying clinical reasoning based on visual observation via eye-movement modelling examples. Instructional Science 40, 813–827.

[31] Jarodzka, H., Scheiter, K., Gerjets, P., van Gog, T., Dorr, M., 2010. How to convey perceptual skills by displaying experts' gaze data, in: Proceedings of the 31st annual conference of the cognitive science society, pp. 2920–2925.

[32] Kok, E.M., De Bruin, A.B., Robben, S.G., Van Merrienboer, J.J., 2012. Looking in the same manner but seeing it differently: Bottom-up and expertise effects in radiology. Applied Cognitive Psychology 26, 854–862.

[33] Kok, E.M., Jarodzka, H., de Bruin, A.B., BinAmir, H.A., Robben, S.G., van Merriënboer, J.J., 2016. Systematic viewing in radiology: seeing more, missing less? Advances in Health Sciences Education 21, 189–205.

[34] Kundel, H.L., Nodine, C.F., Carmody, D., 1978. Visual scanning, pattern recognition and decision-making in pulmonary nodule detection. Investigative radiology 13, 175–181.

[35] Kundel, H.L., Nodine, C.F., Toto, L., 1991. Searching for lung nodules. the guidance of visual scanning. Investigative radiology 26, 777–781.

[36] Nodine, C.F., Kundel, H.L., Mello-Thoms, C., Weinstein, S.P., Orel, S.G., Sullivan, D.C., Conant, E.F., 1999. How experience and training influence mammography expertise. Academic radiology 6, 575–585.

[37] Orlov, P.A., Bednarik, R., 2016. Screenmasker: An open-source gaze-contingent screen masking environment. Behavior research methods 48, 1145–1153.

[38] Otto, K., Castner, N., Geisler, D., Kasneci, E., 2018. Development and evaluation of a gaze feedback system integrated into eyetrace, in: Proceedings of the 2018 ACM Symposium on Eye Tracking Research & Applications, pp. 1–5.

[39] Palmeri, T.J., Wong, A.C., Gauthier, I., 2004. Computational approaches to the development of perceptual expertise. Trends in cognitive sciences 8, 378–386.

[40] Parikh, S., Kalva, H., 2018. Eye gaze feature classification for predicting levels of learning, in: InProceedings of the 8th Workshop on Personalization Approaches in Learning Environments (PALE 2018).

[41] Qvarfordt, P., Biehl, J.T., Golovchinsky, G., Dunningan, T., 2010. Understanding the benefits of gaze enhanced visual search, in: Proceedings of the 2010 Symposium on Eye-Tracking Research & Applications, pp. 283–290.

[42] Ryu, D., Mann, D.L., Abernethy, B., Poolton, J.M., 2016. Gaze-contingent training enhances perceptual skill acquisition. Journal of vision 16, 2–2.

[43] Santini, T., Brinkmann, H., Reitstätter, L., Leder, H., Rosenberg, R., Rosenstiel, W., Kasneci, E., 2018. The art of pervasive eye tracking: unconstrained eye tracking in the austrian gallery belvedere, in: Proceedings of the 7th workshop on pervasive eye tracking and mobile eye-based interaction, pp. 1–8.

[44] Sharma, K., Alavi, H.S., Jermann, P., Dillenbourg, P., 2016. A gaze-based learning analytics model: in-video visual feedback to improve learner's attention in moocs, in: Proceedings of the Sixth International Conference on Learning Analytics & Knowledge, pp. 417–421.

[45] Sibert, L.E., Jacob, R.J., 2000. Evaluation of eye gaze interaction, in: Proceedings of the SIGCHI conference on Human Factors in Computing

Systems, pp. 281–288.

[46] Sowden, P.T., Davies, I.R., Roling, P., 2000. Perceptual learning of the detection of features in x-ray images: a functional role for improvements in adults' visual sensitivity? Journal of Experimental Psychology: Human perception and performance 26, 379.

[47] Turgeon, D.P., Lam, E.W., 2016. Influence of experience and training on dental students' examination performance regarding panoramic images. Journal of dental education 80, 156–164.

[48] Waite, S.A., Grigorian, A., Alexander, R.G., Macknik, S.L., Carrasco, M., Heeger, D., Martinez-Conde, S., 2019. Analysis of perceptual expertise in radiology–current knowledge and a new perspective. Frontiers in human neuroscience 13, 213.

[49] Waldin, N., Waldner, M., Viola, I., 2017. Flicker observer effect: Guiding attention through high frequency flicker in images, in: Computer Graphics Forum, Wiley Online Library. pp. 467–476.