In The Eyes of Experts: Teaching Dynamic Features in Biology by Modeling Experts' Eye Movement Strategies to Novices

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In biology education, it is crucial to be able to classify objects based on complex visual information (e.g., shapes and locomotion patterns of fish). Usually, this ability is trained with books displaying static features and only explaining dynamic features. However, for many classification tasks the dynamic features are very important. Therefore, the overall aim of the two studies described in this paper was to develop an innovative instructional technique for teaching classification skills to students using dynamic visualizations. In order to develop this technique, the first study was conducted to analyze classification processes of experts and novices in detail. This was done by investigating process-oriented differences between experts and novices using eye movements and verbal data obtained during classifying the locomotion pattern of different types of fish. In a second study the process data of experts are replayed to novices in order to support novices in adapting experts' classification strategies.

Classifying Natural Objects in Biology According to Dynamic Features

In biology education, a pivotal skill that students need to acquire during their university training consists in classifying natural objects (e.g., fish) according to complex static and dynamic visual features (e.g., shapes, locomotion patterns). Traditionally, these skills are trained with static pictures and complex identification keys that comprise schematic line drawings of the relevant characteristics. However, for many classification tasks dynamic features are also very important. Therefore, the development of an innovative instructional technique for teaching classification skills to students using dynamic features is a challenge for biology education. Unfortunately, experts' performance on classification tasks is highly automated, and therefore not easy to verbalize or describe. Accordingly, the focus in the first study is on the underlying processes involved in experts' task performance. These processes were first captured and analyzed in detail based on a combination of verbal protocols and eye tracking data. In a second study the process data obtained by this method are used to support novices in analyzing fish locomotion patterns.

Diagnosing Strategies in Inspecting Dynamic Scenes – Study 1

Numerous studies have already been conducted on the topic of expertise (for an overview see e.g., Reimann, 1998). These studies revealed several differences between experts and novices. One important finding is that expertise is acquired through long lasting training, whereby more and more knowledge is summarized and organized in schemata. DeGroot (1978) found important general differences between experts and novices in chess problem solving, that for instance experts solve problems faster than novices because they perceive larger and meaningful patterns; they also possess chunks of related patterns and are able to recognize them within problems. Due to the acquisition of these complex and highly integrated knowledge structures, experts can use many shortcuts in problem solving. With regard to the task of classifying biological locomotion patterns this might imply that experts do not need to go through a complete decision tree, but rather can use knowledge-based shortcuts for classification (*cf.* findings from medical diagnosis; Schmidt, Norman, & Boshuizen, 1990). In order to uncover the problem solving processes deployed by experts, usually verbal expressions during problem solving, so called verbal protocols are obtained (Ericsson & Simon, 1980). However, with increasing expertise and at the same time increasing automation of schemata application, these processes become less accessible for verbalization (Ericsson & Simon, 1980). Since, the focus in this paper is on a highly visual task, namely classification of biological locomotion patterns, this lack in accessibility for verbalizations might be even more severe. Hence, verbal protocols alone may not be a sufficient method for capturing classification processes of experts. Therefore, we decided to additionally capture experts' visual strategies in a more direct way by means of eye tracking. Since, the classification of biological locomotion patterns is a complex knowledge-based visual task a combination of verbal protocols with the analysis of eye movements might be an appropriate method. In line with this reasoning, Van Gog, Paas, and Van Merriënboer (2005) concluded that the combination of verbal reports and eye movement data provides promising insights into expertise acquisition in different domains and allows to derive novel guidelines for instructional design. Therefore, the aim of our first study was to analyze eye movements and verbal protocols of experts and novices during a biological classification task.

However, it remains an important open issue to what extent it is possible to infer the underlying cognitive processes and knowledge structures from eye movement pattern. According to Yarbus (1967) the relation between eye movements and cognition is notably reliable for task-relevant looking. In this case the human eye has to align itself actively and directly to the stimulus currently to be processed, so that the focus of attention captured by eye tracking may be appropriate to reveal cognitive processes. Since participants in our study had to conduct a visual classification task, we assume that at least some inferences from their eye movements to the cognitive strategies involved in classification are possible. However, due to the highly integrated knowledge structures of experts it may occur that experts use knowledge-based shortcuts to classify biological locomotion patterns without even attending to the relevant dynamic features of the stimulus. For instance, experts might easily recognize a particular species due to some prominent static features (e.g., a specific pattern of colorful body stripes characteristic for a particular fish species). Upon his highly integrated schematic knowledge about different fish species, the expert might not need to observe the locomotion pattern of this fish in detail, since based on his schematic knowledge the expert simply *knows* how this fish species swims without further perceptual processing. For a novice, this type of knowledge-based problem solving shortcut will not be available. The novice will rather need to scan the entire fish for moving parts. Consequently, we have to keep in mind that the visual strategies of experts as they can be registered by means of eye tracking result from a combination of perceptual processing and knowledge-based processing operating on highly integrated schematic knowledge structures.

In sum, it is assumed that different levels of expertise with regard to a biological classification task will be reflected in different eye movement patterns. In particular experts should solve classification problems faster, and thus need less time to describe and classify biological locomotion patterns (*cf.* deGroot, 1978). Moreover, it is assumed that experts use knowledge-based shortcuts, like immediately associating a biological species recognized from static features with a certain locomotion pattern. Furthermore, it is assumed that there is an effect of different expertise levels on verbal data. It is expected that experts verbalize less than novices due to schema automation (Ericsson & Simon, 1980). However, it is expected that experts' verbalizations will be more accurate than those of novices (*cf.* Johnson, 1988). These assumptions are investigated in Study 1 in the domain of fish locomotion pattern.

Participants and Design

Fourteen participants (*M* = 27.21 years, *SD* = 7.29 years; 6 women and 8 men) with two different levels of expertise took part in the first study. Eight of them were biology freshmen of the University of Tuebingen, Germany with an average age of 23.5 years (*SD* = 1.60), who already took part in an elementary fish classification course and therefore had a rough idea of fish anatomy and the respective terminology. They participated for payment (10 Euro) and were classified as novices. Six persons, classified as experts, with an average age of 32.17 years (*SD* = 9.11), were at least doctoral candidates within this domain and participated voluntarily. Assignments of the participants to different expertise levels were conducted by a professor of Marine Biology. Additionally, the expertise level of the participants was validated by means of a questionnaire. As dependent variables process data from two sources were obtained: eye tracking and verbal protocols.

Materials and Apparatus

The stimulus material used in this study consisted of four videos (for screen shots see Figure 1) shown in an audio video interleave format (AVI) on an eye tracker monitor (the areas of interest displayed in Figure 1 where not visible to the participants). Each video depicted an individual fish during swimming whereby each of the four fish was characterized by a different locomotion pattern (i.e., tetraodontiform, subcarangiform, labriform, and balistiform). The duration of each video was eight seconds on average. The videos looped automatically. The participants' task was to classify or describe the fish locomotion pattern as soon as they felt able to do so. Eye movements during watching the videos were recorded with a Tobii 1750 eye tracking system, which captured eye movements in an unintrusive way by recording them with invisible cameras integrated in the monitor frame. Verbal data were recorded with the Camtasia software using a standard microphone. In order to assess possible control variables a questionnaire was administered. This paper and pencil questionnaire consisted of 12 items, including demographic data (age, gender), experience (number of oceanic dives, possession of aquarium, possession of fishing license, educational degree in biology), interest (frequency of snorkeling, frequency of watching movies on the topic, and frequency of reading about fish), and subjectively estimated expertise regarding the domain of fish locomotion.

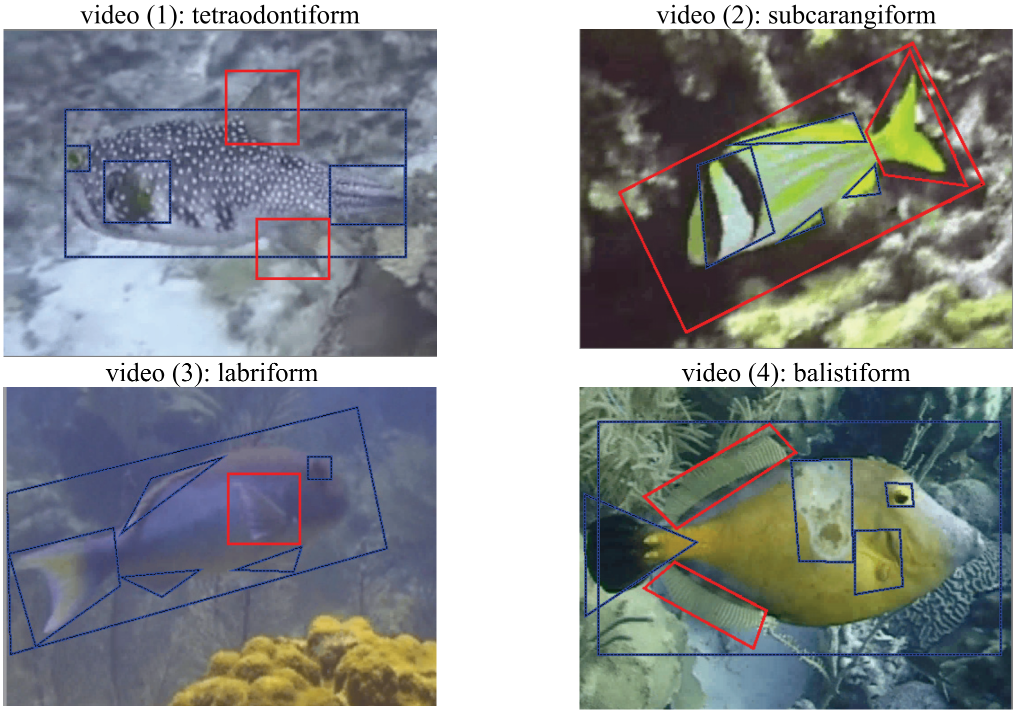

Figure 1. Screenshots from videos used in Study 1 (with areas of interest displayed).

Procedure

After participants had been welcomed and the procedure had been described to them, they filled in the questionnaire. Subsequently, the eye movements of the participants were calibrated. Afterwards, they watched the four videos, while being eye tracked. The videos looped automatically, so participants could decide for themselves on how long they wanted to watch each video. After having watched each of the videos, participants had to describe the locomotion pattern of the depicted fish before continuing with the next video.

Results

Questionnaire Data

Differences in the questionnaire data within the groups are displayed in Table 1. Item (1) was an open question, items (2) and (3) had a dichotomous response format, items (4) to (9) had a six-point Likert-scale response format with answers ranging from "strongly disagree" to "strongly agree". From these results it follows that experts had completed significantly more oceanic dives, (F (1,12) = 18.84, p < .01), were significantly more interested in fish (F (1,12) = 46.94, p < .01), did more snorkeling (F (1,12) = 88.17, p < .01), read more about fish (F (1,12) = 10.26, p < .01), and rated their own knowledge on fish locomotion higher (F (1,12) = 39.47, p < .01) than novices. Thus, substantial differences between experts and novices were confirmed by this set of data.

Table 1: Means and standard deviation for the questionnaire data.

	Experts	*Novices*	*p*
(1) Current number of oceanic dives	240.50 (154.07)	5.63 (15.91)	< .01
(2) Possession of an aquarium	1.67 (0.52) [1]	1.75 (0.46) [1]	.76
(3) Possession of a fishing license	2.00 (0.00) [1]	2.00 (0.00) [1]	[2]
(4) I'm very interested in fish.	5.83 (0.41)	2.75 (1.04)	< .01
(5) I snorkel very often.	5.17 (0.98)	1.38 (0.52)	< .01
(6) I watch movies or documentaries about fish very often.	4.33 (1.51)	2.88 (1.36)	.27
(7) I visit aquaria very often.	3.50 (1.23)	2.75 (1.17)	n.s.
(8) I read a lot about fish (books, internet).	3.83 (0.98)	2.13 (0.99)	< .01
(9) I know a lot about typical patterns of fish locomotion.	5.00 (1.27)	1.63 (0.74)	< .01

Note: [1] "yes" was coded as 1, "no" was coded as 2; [2] could not be analyzed due to lack of variance

Verbal Data

Verbal data were coded in the following manner: Naming the correct technical term, which describes the locomotion pattern, was coded as 1, whereas naming a wrong technical term or none was coded as 0. The remaining verbal data obtained from the descriptions of the locomotion pattern were coded in two ways. First, it was coded whether participants described correctly *which* part of the fish body moved. Second, it was coded whether participants described correctly *how* the part of the fish body moved. Again, the correct answer was coded with 1, a correct but colloquial description was coded with 0.5, and everything else was coded with 0. The coding system is summarized in Table 2.

Table 2: Coding system for verbal data.

	Technical term?	*What moves?*		*How does it move?*	
coding	1	1	0,5	1	0,5
video (1)	tetraodonti	anal and dorsal fin	e.g., upper and lower fin	oscillating	e.g., moving like a paddle
video (2)	subcarangi	caudal fin	-	undulating	e.g., wavelike
video (3)	labri	pectoral fins	-	oscillating	e.g., moving like a paddle
video (4)	balisti	anal and dorsal fin	e.g., upper and lower fin	undulating	e.g., wavelike

Results show that experts knew significantly more technical terms for the locomotion patterns (F (1,12) = 10.01, $p < .01$; *cf.* Table 3). This indicates that novices lack factual knowledge about fish locomotion. Furthermore, results show that novices, compared to experts, were not able to recognize which parts of the fish body are important for the locomotion (F (1,12) = 11.42, $p < .01$). This indicates a need for attentional guidance for novices. On the other hand, experts and novices did not differ in the way they described how the parts of the fish body move, although both groups barely described it. This might be due to the fact that the technical term already included the locomotion pattern by definition. However, novices did not express the technical term; therefore they obviously need additional information on different locomotion pattern during watching the videos.

Table 3: Mean number (SD) of correct descriptions for all four videos.

Coding	*Experts*	*Novices*	*p*
Technical term?	1.33 (1.21)	0.00	< .01
What moves?	4.00 (0.00)	2.36 (1.28)	< .01
How does it move?	1.08 (1.11)	1.21 (1.04)	.83

Eye Tracking Data

Eye tracking data were analyzed using Clearview 2.70 software. Novices had significant longer mean viewing times per video than experts (F (1,13) = 17.17, $p < .01$; *cf.* Figure 2).

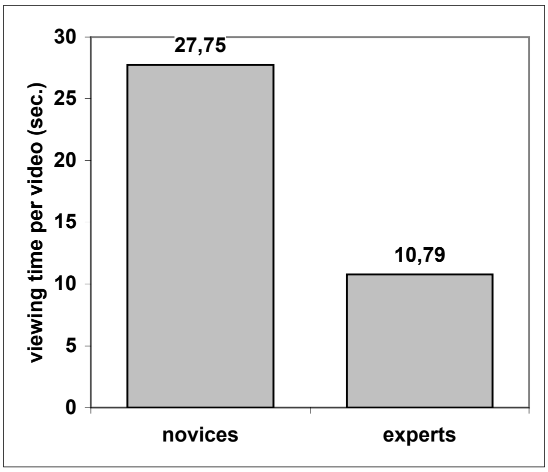

Figure 2. Mean viewing time per video in sec.

To analyze the eye-tracking data in greater detail, we defined separate areas of interest (AOIs) for each of the four videos. AOIs are precisely defined areas on the object (e.g., one fin) that are used to summarize parameters like number of fixations or viewing times. For instance, Figure 3 displays differentiated results for different AOIs in video 2. The chart represents a difference measure, namely experts' viewing times for different areas of interest subtracted from the viewing times of novices. Thus, the focus is on the difference between both groups. Bars above the zero-line indicate that novices looked longer on the AOIs represented by the bars, whereas bars below the zero-line indicate that experts looked longer on these AOIs. For instance, novices paid more attention to the body (F (1,14) = 3.99, p = .07) and the caudal fin (F (1,14) = 8.57, p = .01) than experts. These two parts of the fish body are crucial for the classification of the locomotion pattern shown in video 2. However, although novices focused their visual attention on the relevant parts of the fish body in video 2, their verbal data indicated that they were not able to recognize them as crucial. Experts on the other hand paid more attention to the stripes on the fish body than novices (F (1,14) = 1.83, p = .20). These stripes are a static feature that is not crucial for the classification of the locomotion pattern, however, it allows for the classification of the fish species. Therefore, the approach that the experts took in analyzing video 2 might be an example confirming the assumption that experts tend to use knowledge-based shortcuts in movement classification that are unavailable to novices. For instance, in video 2 experts might have chosen to focus on a feature that is unique for a particular species (i.e., the stripes) and that allows them to infer the locomotion pattern of the fish from this knowledge about the species without looking in detail at the moving parts of the fish body. However, these shortcuts that show up in experts' eye movement data pose some problems for the idea of using experts' gaze patterns as instructional materials for novices. As novices do not possess the knowledge structures yet that enable the shortcuts, a gaze replay of an expert might be of very limited use as training material for a novice. This issue is addressed in Study 2.

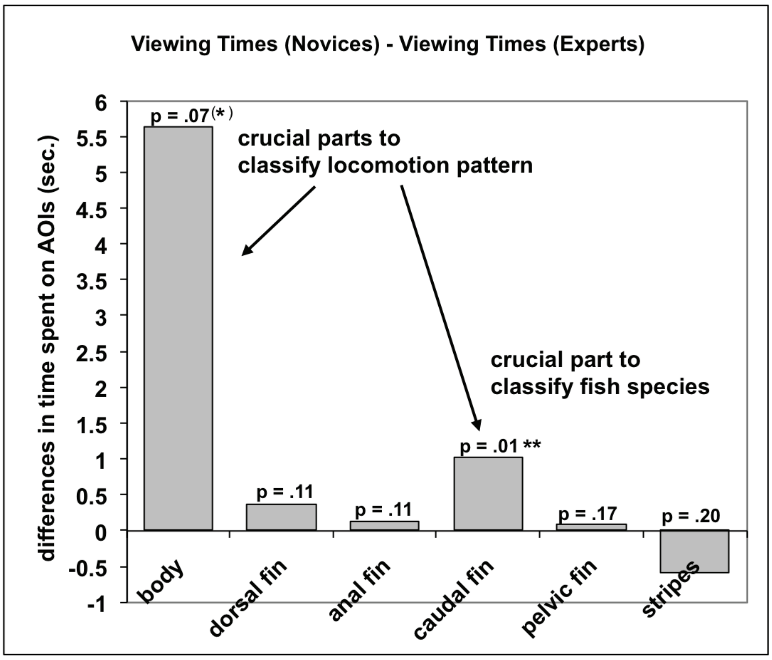

Figure 3. Differences between experts and novices in gaze durations per AOI in video 2.

Process Training Through Eye-Movement Modeling – Study 2

In a second study, the novel approach of supporting knowledge acquisition based on eye movement modeling (EMM) is addressed more directly. The basic idea of this approach is to replay eye movements of experts to novices. Novices then may follow these gazes with their own eye movements. Mirroring the eye movement pattern of experts, in turn, might facilitate the acquisition of expert strategies for novices.

Findings from worked examples research and considerations based on cognitive load theory support this approach. According to cognitive load theory (Sweller, Van Merriënboer, & Paas, 1998), meaningful learning presupposes that the working memory's capacity is not exceeded, particularly not by extraneous cognitive load (ECL) which hinders learning and can be reduced by appropriate instructional design. The reduction of ECL can for instance be achieved by presenting worked examples (Atkinson, Derry, Renkl, & Wortham, 2000). In worked out examples learners are given problems together with an optimal solution strategy usually observed in experts. In particular, the presentation of process-oriented examples may be helpful for learning. Process-oriented examples do not only present a solution procedure but also comprise the reasoning processes that led to this procedure (Gerjets, Scheiter, & Catrambone, 2004; Hoogveld, Paas, & Wim, 2005). In line with this reasoning, the idea of EMM can be seen as the provision of a perceptual process-oriented worked example (*cf.* Van Gog, 2006).

In addition, this approach of replaying eye movement patterns of experts may also be viewed as an innovative kind of cognitive modeling. Cognitive modeling is based on observational learning (Bandura, 1997). Bandura (1997) showed that observing a model performing a task already leads to learning, without having ever performed this task before. This may also be true for observing process data related to cognitive tasks, for example verbal protocols or eye-movement data. The presentation of modeling depends on the task, for example the strategies can be simply described or experts themselves can be shown on videos solving the problem and explaining how and why they do it (Van Merriënboer, 2002). Presenting gaze replays of experts can be considered an innovative representational format for modeling. According to the cognitive apprenticeship approach (Collins, Brown, & Newman, 1987) experts often fail to uncover important tacit knowledge (i.e., knowledge that is difficult to access) which might hinder learning. Eye movement modeling might be a suitable method to reveal tacit perceptual knowledge of experts to novices.

However, there might also be some challenges in implementing the approach of EMM. First, as results from Study 1 showed experts seem to use knowledge-based shortcuts in their task performance. Due to novices' lack of the relevant knowledge that prevents them from using these shortcuts, raw eye movements may not be useful for modeling purposes. Consequently, experts might need to be instructed to "behave more didactical" before their eye movements are recorded. For instance, current studies on expert behavior in writing processes state that already rather subtle instructions, that is, only reminding experts that the results of their behavior will be presented to novices, change their behavior dramatically (Jucks, Schulte-Löbbert, & Bromme, in press). This may be also true for eye movements. Second, even if novices know where they should look at, they still might lack relevant schematic knowledge that would allow them to meaningfully interpret what they see. For instance, in Study 1 novices focused their visual attention on the relevant parts of the fish body, their verbal data, however, indicated that they were not able to recognize them as crucial. Thus, even if novices are instructed where to look they still might not know *why* they should look at a certain area and *what* information can be obtained from focusing that area. Hence, additional information is needed. This information can be provided on the basis of verbal protocols of experts that received an instruction for didactical behavior. These protocols might serve as cues in order to help solving highly complex visual tasks. Additionally, they might offer instructional explanations. Thus, a combined presentation of gaze replays and verbal protocols should be particularly beneficial to learners.

In line with this reasoning, the following research questions will be addressed in Study 2: First, it is expected that gazes of novices align to expert gazes presented during learning. This would result in more homogenous gaze patterns compared to a control group learning from video materials without gaze replay. Second, it is expected that modeling by means of experts' gazes leads to better learning outcomes only when the experts received a specific didactical instruction. Receiving gaze replays of uninstructed experts, however, might even result in worse learning outcomes, since the shortcuts that experts might use have the potential to distract novices from concentrating on important features of the stimulus. Third, it is expected that verbal explanations lead to better learning outcomes for both types of EMM (with and without didactical instruction) compared to a condition without modeling. Without EMM the verbal explanation might even confuse learners because the may not know to which part of the visual stimulus the verbal explanations refer. This might lead to worse learning outcomes.

Design

In the second study, two factors will be varied resulting in a 2*3 design. The first factor is verbal explanation (with vs. without). The second factor is EMM (without gazes vs. gazes of uninstructed experts vs. gazes of instructed experts). Dependent variables arise from two sources: posttest data and eye tracking data. The posttest comprises factual knowledge assessed by text-based questionnaires. In addition, visual tests are involved in order to capture the mental model of the locomotion pattern built during learning. Furthermore, eye-tracking data will be collected.

Material and Apparatus

The material for the second study is currently under construction. It is designed as a browser-based learning environment that can be presented on a standard computer. The experiment will start with a questionnaire on demographic data and important control variables (*cf.* first study). Subsequently, a short introduction to basic technical terms of fish physiology, underlying physical principles, and a rough description of different locomotion patterns will be presented. This will be followed by the learning phase where the four locomotion patterns used in Study 1 will be taught. For each locomotion pattern, a short textual description will be presented (i.e., the technical term of the locomotion pattern). Then, a video of a swimming fish will be displayed according to one of the six experimental conditions. This procedure will be repeated for all four videos (*cf.* first study). Afterwards, participants will be asked to describe each swimming mode. Furthermore, factual knowledge will be measured by means of multiple choice tests and by means of recognizing locomotion pattern of known and unknown fish (video based).

Results

This study is currently in preparation and will be conducted in December 2007. The results will be presented at the conference.

General Discussion

This paper aims at developing a novel method for facilitating the acquisition of expert strategies in the domain of classifying biological locomotion pattern. This method is based on the idea of using experts' eye movement pattern as instructional material to model their perceptual strategies to novices. In order to develop learning materials to implement this method, a first study was conducted to identify differences between experts and novices with regard to verbal data and eye movements during the classification of fish locomotion pattern.

Results show that process data differ as a function of expertise levels. Results from verbal data show that experts are well able to name the locomotion pattern using the correct technical term. Not surprisingly, novices were not able to do so. Moreover, results show that compared to experts, novices are not able to identify the parts of the fish body relevant for locomotion. This leads to the assumption that attentional guidance for novices is needed, which can be achieved by EMM. Surprisingly, experts and novices both refrained from describing the locomotion pattern appropriately. However, this finding might go back to different reasons for experts and novices. For experts, who often named the correct technical term of a locomotion pattern, the finding might be due to the fact that the technical term already includes the locomotion pattern by definition. However, novices did not express the technical term. So, they just might not be able to describe a locomotion pattern appropriately. Therefore, they might need additional instructional explanation during watching the videos. Results with regard to eye movement data show that experts do not necessarily focus on the AOIs crucial for identifying a locomotion pattern. Instead they might concentrate on features that are not related to locomotion pattern but allow to identify the fish species displayed. This finding seems to contradict previous research that often shows that increasing expertise results in ignoring irrelevant information. This has been shown in different domains, like arts (Antes & Kristjanson, 1991) and motion recognition in gymnastics (Moreno, Reina, Luis, & Sabido, 2002). Haider and French (1999) found that this effect arises at a perceptual level already. However, the contrasting findings we obtained might be due to the specific task of classifying locomotion patterns. As deGroot (1978) already found, experts solve problems faster than novices since they perceive complex and meaningful patterns; and possessing chunks of related patterns enables them to recognize the patterns within problems. Therefore, experts probably do not need to focus on the body parts for identifying a locomotion pattern as they can use different kinds of shortcuts due to their expertise.

The findings from Study 1 led to the assumption that merely watching an expert solving a problem in her/his own way may not be exceptionally useful for novices. Thus, additional instructions for experts to "behave in a more didactic manner", are needed. This procedure has shown to be successful in a different domain, namely writing processes of experts for novices (Jucks, Schulte-Löbbert, & Bromme, in press). In this field, even subtle manipulations lead to dramatic changes in experts' behavior. Additionally, attention direction may not be sufficient, as verbal data from the first study revealed. Directing the attention of novices to important parts of a video does not necessarily mean that relevant schemata will be activated. Therefore, additional information has to be offered to novices, for instance by providing them with additional instructional explanations as will be done in Study 2.

In sum, up to now very little is known about the promising approach of supporting learners by means of EMM. Further research is needed in order to examine different presentation formats for gaze replays as well as different ways of offering additional verbal information that can be combined with gaze replays.

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