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Identification of effective visual problem solving strategies in a complex visual domain

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A B S T R A C T

Students in complex visual domains must acquire visual problem solving strategies that allow them to make fast decisions and come up with good solutions to real-time problems. In this study, 31 air traffic controllers at different levels of expertise (novice, intermediate, expert) were confronted with 9 problem situations depicted on a radar screen. Participants were asked to provide the optimal order of arrival of all depicted aircrafts. Eye-movements, time-on-task, perceived mental effort, and task performance were recorded. Eye-tracking data revealed that novices use inefficient means-end visual problem solving strategies in which they primarily focus on the destination of aircraft. Higher levels of expertise yield visual problem solving strategies characterized by more efficient retrieval of relevant information and more efficient scan paths. Furthermore, experts' solutions were more similar than intermediates' solutions and intermediates' solutions were more similar than novices' solutions. Performance measures showed that experts and intermediates reached better solutions than novices, and that experts were faster and invested less mental effort than intermediates and novices. These findings may help creating eye-movement modeling examples for the teaching of visual problem solving strategies in complex visual domains.

1. Introduction

In many complex cognitive domains, professionals (e.g., medical specialists, power plant controllers, pilots) make decisions on the basis of their interpretation of complex visualizations. Air traffic controllers, for example, need to interpret available visual information on a radar screen in order to guide aircraft to an airport. Students in air traffic control (ATC) must develop domain-specific visual problem solving strategies to become experts in their domain. Process-oriented worked examples that make the cognitive processes of experts visible can help students learn to solve particular problems (Van Gog, Paas, & Van Merriënboer, 2006, 2008; Van Gog & Rummel, 2010). In visual domains, eye-movements are a direct indicator of visual expertise because they change as experience increases from novice towards expert (for overviews, see Gegenfurtner, Lehtinen, & Säljö, 2011; Gegenfurtner, Siewiorek, Lehtinen, & Säljö, 2013; Reingold & Sheridan, 2011; Spivey & Dale, 2011). So-called eye-movement modeling examples (EMMEs) may make the visual problem solving process visible by superimposing an expert's gaze pattern on the image so that the learner can study what an expert is looking at and in which order (Jarodzka et al., 2012; Jarodzka, Van Gog, Dorr, Scheiter, & Gerjets, 2013; Van Gog, Jarodzka, Scheiter, Gerjets, & Paas, 2009). However, there are open questions in terms of how to design EMMEs using experts' eye-movements. The first question concerns the strategies for visual problem solving used at different levels of expertise (Feldon, 2007; Jarodzka, Scheiter, Gerjets, & Van Gog, 2010). The second question is whether these strategies lead to one common solution or to a wide variety of solutions when carrying out a perceptual task (cf. Medin et al., 2006).

With regard to strategies used at different levels of expertise, at least three levels can be distinguished in the development towards expert performance (Berliner, 1986; Boshuizen & Schmidt, 2008; Dreyfus & Dreyfus, 2005). Novices are beginners in a domain without relevant experience; they gradually build up a large amount of knowledge which is represented in networks that result

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in long chains of detailed reasoning steps. Intermediates have already acquired first experiences in a domain, which allows them to encapsulate parts of their knowledge leading to shortcuts in reasoning and thus higher performance. Experts' knowledge is stored in an entirely different, but very efficient manner, namely in scripts (Boshuizen & Schmidt, 2008), enabling them to show "consistently superior performance on a specified set of representative tasks for a domain" (Ericsson & Lehmann, 1996, p. 277). Most research on visual problem solving focused on experts only or on differences between novices and experts. The number of studies using intermediates is limited (Gegenfurtner et al., 2011; Reingold & Sheridan, 2011), and, thus, there is a lack of knowledge about stages in the development of visual problem solving as well as the strategies novices, intermediates and experts use when solving visual problems. This knowledge is needed for designing example-based learning materials such as EMMEs. Moreover, it is important to know whether particular visual problem solving strategies lead to different solutions for the same problem or not; obviously, it is more desirable to teach problem solving strategies that lead to similar and good solutions for a wide range of problems.

This article aims at gaining insight in how expertise affects visual problem solving strategies, similarity of found solutions, and performance. The next sections discuss the visual problem solving strategies novices, intermediates and experts use when carrying out perceptual tasks; the degree to which people with different expertise levels and strategies come up with either common or different solutions for the problem at hand, and the moderating effect of task difficulty when studying the influence of expertise on visual problem solving strategies, the similarity of solutions, and performance.

1.1. Visual problem solving strategies

When solving problems, cognitive schemas retrieved from long-term memory enable the use of problem solving strategies (Boshuizen & Schmidt, 2008). At least three problem solving strategies can be distinguished for solving visual problems, namely, attention focusing, chunking, and means-end analysis (Chi, Glaser, & Rees, 1982; Gobet & Simon, 1998; Haider & Frensch, 1999; Simon, 1975).

When using the strategy *attention focusing* schemas help to distinguish between relevant and irrelevant information and so enable problem solvers to focus on what is important in a given problem situation. Haider and Frensch (1999) describe in their *information-reduction* theory that experts optimize the amount of processed information by separating task-irrelevant from task-relevant information. This theory was supported by the findings in a meta-analysis by Gegenfurtner et al. (2011) and by Reingold and Sheridan's (2011) review of research on expertise in medicine and chess. In the field of aviation, two studies support the information-reduction theory. Kasarskis, Stehwien, Kickox, and Aretz (2001) studied scanning characteristics of novice and expert aircraft pilots during landing. They found that eye-scanning patterns and specific fixation behaviors of experts differed from those of novices. Experts showed shorter but relatively more eye-fixations (during fixations the eyes stand still and take in new information), more eye-fixations on relevant points such as aim point and airspeed, and fewer fixations on less relevant points such as the altimeter because all necessary altitude information was obtainable from the true horizon. Also in a study by Bellenkes, Wickens, and Kramer (1997), expert pilots scanned more crucial instruments during a simulated flight task than novices. In ATC the use of information reduction could show in experts fixating faster on relevant objects (i.e., aircraft) and fixating them relatively longer.

The strategy of *perceptual chunking* relevant information, described as *unitization* by Goldstone (1998), makes it possible to combine important elements together so that they can be treated in working memory as *one* information element in a given problem situation. This requires less effort than processing all elements separately. For example, experts in chess are known to become familiar with complex configurations of separate chessmen and they are able to recognize these configurations as single units (Jongman, 1968). Hence, experts use schemas formed from earlier experiences and recognize familiar compositions of task elements or 'patterns' (e.g., frequently occurring air traffic situations) without viewing all the details (Gobet & Simon, 1998). In ATC, the use of perceptual chunking would be manifest in less gaze switches (i.e., transitions) between separate elements (e.g., aircraft), because particular groups of elements (e.g., all aircraft in a queue) are perceived as one element (i.e., chunk).

The strategy that can be characterized as *means-end analysis* is based on schemas for working backward from the goal, rather than working towards the goal. This strategy is described as a highly general but effort-demanding problem solving strategy (Simon, 1975), where the task performer uses a continuous orientation on the goal (the 'end') and tentatively applies operators (the 'means') to determine a next step in the problem solving process that helps to move in the direction of the goal. More advanced problem solvers understand which routine of operations is underlying the final solution. Thus, they do not reason backwards from the goal but decide based on the prior act what the next act should be to reach the final goal. This sequence of actions can ultimately become automated, leading to fast and accurate performance which hardly requires the investment of mental effort (Chi et al., 1982; Sweller, 2004; Van Merriënboer, Clark, & De Croock, 2002). In a visual domain like ATC, the use of means-end analysis would be manifest by frequently focusing (i.e., more eye-fixations) on the goal (e.g., the airport), whereas working-forward strategies would be manifest by frequently focusing on the elements that are affected by the problem solving steps (e.g., the aircraft).

1.2. Similarity of solutions

For problems in complex visual domains, there is typically not one general problem solution but a broad range of solutions that may vary from suboptimal (or even incorrect) to more optimal (Gronlund, Dougherty, Durso, Canning, & Mills, 2005; Mumford, Schultz, & Van Doorn, 2001). In ATC, for example, the number of acceptable solutions to guide the aircraft to an airport is restricted by safety rules and the need for efficiency (safety: maintaining at least five miles horizontal separation and 1000 feet vertical separation; efficiency: causing as little delays as possible), but there are many degrees of freedom in finding these solutions (e.g., you can keep enough separation between aircraft by changing either their speed, height or direction).

The level of expertise influences the ability of anticipating on possible situations (Mumford et al., 2001) resulting in more or less optimal solutions. For novices, visual problem solving is highly demanding because they have not yet cognitive schemas available that help them organize the perceived information. Due to their limited working-memory capacity they are easily overwhelmed by the amount of information, especially when this information is transient such as in ATC (Lowe, 2003; Mayer, 2005; Scheiter, Gerjets, Huk, Imhof, & Kammerer, 2009; Spanjers, Van Gog, & Van Merriënboer, 2010; Sweller, Van Merriënboer, & Paas, 1998). As a consequence, their awareness of the current situation will be limited, incomplete and sometimes erroneous, which hampers their projection of the future status (Endsley, 1995) and thus leads to a broad range of dissimilar solutions, including many incorrect or suboptimal solutions.