Geo-Collaboration under stress

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ABSTRACT

> "Most of the science and decision making involved in geo-information is the product of collaborative teams. Current geospatial technologies are a limiting factor because they do not provide any direct support for group efforts." ----- [18]

In this paper we present a method to enhance geo-collaboration by communicating relevant info about users to other team members. We give examples on how knowledge about the cognitive load, affective load, location, and task relevant information of the user can enhance geo-collaboration. Next we give a short literature review of geo-collaboration research. This is followed by a section about critical state recognition with the use of a cognitive task load, an affective task load, and a performance model. We conclude that research is needed to test critical state recognition in the field and see what support is best.

Categories and Subject Descriptors

H.1.2 [**Information Systems**]: User/Machine Systems – *Human Factors.*

General Terms

Performance, Human Factors, Theory

Keywords

Collaboration, Critical state recognition, Stress, Emotion

1. INTRODUCTION

Imagine an emergency situation such as a fire or an earthquake. Teams of rescue workers are sent into the field to do urban search and rescue (USAR) in the area. To search the area as fast as possible a work area is assigned to each of the team members.

Physiologically, cognitively, and psychologically rescue work is a demanding task [19]. With a mobile system that displays a map the rescue workers can see where the other team members are, what their state is, and what their assigned search range is. Furthermore, the rescue workers can indicate points of interest, such as locations where victims are found (dead or alive). This information can be communicated to the team.

The state of the user influences his/her preferences and performance. Firstly, the search range that a rescue worker is able to search through depends on the cognitive and affective task load. For example, searching for victims in collapsed buildings is physiologically and cognitively more demanding than searching for victims that lay out in the open [19]. The affective task load also influences the search range, since rescuing a victim can boost the performance while finding several dead victims may decrease the performance due to the affective state of the rescue worker. Depending on the decrease or increase in search range, the work areas can be dynamically redistributed, automatically or manually. The redistribution should be visualized on the mobile displays of the team members.

Secondly, knowledge about the task load of the user can enhance the communication between team members. They can decide not to ask for help or share information with a team member, because the team member has a high task load, something that people already do in face-to-face communication: when a passenger in a car sees that there is a demanding situation for the driver he/she stops talking for a moment.

Finally, team members can use knowledge about the task load of another team member to decide helping him/her. If the task load is high or the task load is significantly lower then one would expect he/she might need help. When for example one of the rescue workers is not moving and task load is very low, he or she could be injured.

Recognition of situations wherein the task load of the user is very high, very low, or deviates from the expected task load can enhance geo-collaboration in emergency situations.

2. GEO-COLLABORATION

In the IT Roadmap to a Geospatial future [18] geo-collaboration is identified as essential for teams that discuss geo-information and/or are located at different locations. Furthermore they observed that collaboration is not supported in current geospatial technologies. While for co-located teams and with the increasing usage of mobile devices by professionals this need has increased. In recent years some work has been done on this topic, but it is still a rather underdeveloped field. In this section we present an overview of relevant work for geo-collaboration.

Sharing information between team member using geospatial information enhances the development of common ground and reduces the workload of individual team members for three reasons [14]:

1) Visual representations can support computational offloading, reducing the cognitive load.
2) Visual representations can substantially help to structure a problem to make it comprehensible and increase both individual and group understanding.
3) Visual representations provide limits on the kinds of inferences and interpretations that can be made.

During the planning phase geo-collaboration can be used for decision making [3]. Team members are enabled by the geospatial information to explore the spatial decision problem, experiment with choice alternatives, and formulate alternatives.

Although most geo-collaboration research is focused on the planning phase, real-time information during the execution phase is also important. There is a need to know where team members are, what they are doing, and what their workload is for a successful collaboration [15]. This is important while it gives information about who is available to help, who needs to be relieved from some work, who needs help, and what is the overall state of the mutual goal. In Section 3 we will elaborate on how the state of the user can be recognized.

The geospatial information and the information about team members in both the planning and the execution phase should be visualized in a way that is understandable in a glance. The way of information visualization is dependent on the device a team member has and the information he/she needs, dependent on his/her function and task [4]. With the development of a mobile application the challenges of a small screen for information visualization and interaction should be taken into account [13].

3. CRITICAL STATE RECOGNITION

For the critical state recognition we will use three different models; a cognitive task load model, an affective task load model, and a performance model (Figure 1) to reach robust recognition. All models receive information from context, psychophysiology, and behavior to base their output on [21]. Critical situations are defined by metrics of both a specific type and the match or mismatch between the three types of metrics (e.g. the human may be in an emotional or affective state that is not appropriate for the cognitive demands imposed by the task.

3.1.1 *Cognitive task load*

For the *Cognitive Task Load (CTL)*, three factors prove to determine operator performance substantially [10; 11; 20] (Figure 2). The first factor is percentage time occupied by the task. In addition to the operational and contextual demands, human's cognitive processing speed determines this pressure for an important part, that is, the speed of executing elementary cognitive processes. Particularly, time pressure is high when the processes require a lot of attention and focused concentration. Cognitive processing speed is determined by the individual capabilities to search and compare known visual symbols or

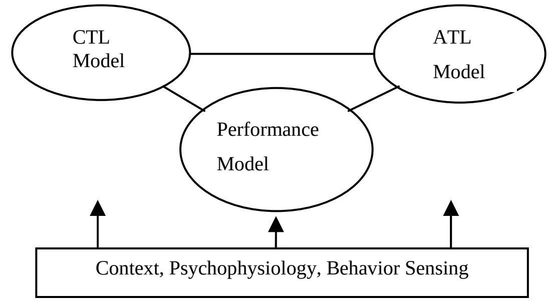

Figure 1 Critical state recognition

CTL = Cognitve Task Load, ATL = Affective Task Load

patterns, to perform simple (decision-making) tasks, and to manipulate and deal with numbers in a fast and accurate way.

Second, the task complexity affects the level of information processing (LIP) (cf. the skill-rule-knowledge framework of Rasmussen [25]) and thereby the cognitive task load. Task information that is processed automatically, results into actions that are hardly cognitively demanding. Performance of routine procedures results into relatively efficient problem solving. Problem solving and action planning for relatively new situations can involve a heavy load on the limited capacity of working memory. Human's expertise and experience with the tasks have substantial effect on their performance and the amount of cognitive resources required for this performance. Higher expertise and experience result in more efficient, less-demanding deployment of the resources.

Third, the CTL theory distinguishes task switching or sharing as a third load factor to address the demands of attention shifts or divergences. Complex task situations consist of several different tasks, with different goals. These tasks appeal to different sources of human knowledge and capacities and refer to different objects in the environment. Switching entails a change of applicable task knowledge. Figure 1 presents the "load" space of the user. When the load is in the middle area of the figure the mental load is not too high or too low. Angular points; 1, 2, and 8 represent respectively underload, vigilance [11], and overload. When both time occupied and task switching are high lockup can appear [20]. The CTL model has been successfully applied in the field [10; 11].

3.1.2 *Affective task load*

In cognitive science emotions were discarded for a long time [30], but research in psychology and neuroscience has identified the crucial role emotion has in decision-making and social interaction. Now it is widely accepted that cognitive processes are closely related to emotions. Emotions are shown to have both positive and negative effects on cognitive processes [1; 6; 28]. Both people with lesions in their emotional system (i.e. "pure rational human beings", see [6], and people with high emotional responses show impaired decision making [1; 28]. As shown by Sorg and Whitney [28] and Al'Absi, et al. [1], stress impairs the working memory. Affective states influence both low-level and higher-level perceptual, cognitive, and motor processes. Affective states can help activate or inhibit particular actions, and perception or processing of specific stimuli. In this way the mental model of the user is influenced by his/her affective state and experimental research has shown that the

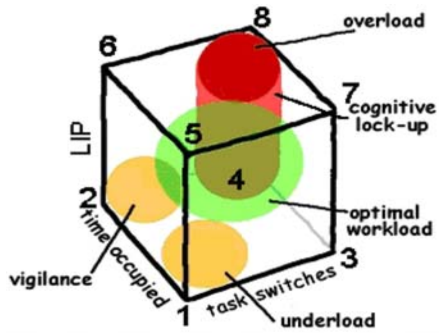

Figure 2 Cognitive Task Load [20]

mental model plays a critical role in decision making [12]. Anxious people have a negative mental model of the world and research shows that they have a bias for negative interpretation of events and items [16].

This shows that *Affective Task Load* (ATL) is also an important factor for critical state detection. For characterizing the ATL, we will focus on the underlying, often physiologically correlated factors (e.g. arousal) and map these onto distinct dimensions. Such dimensional models are helpful in both recognition and expression, as well as in models of emotion generation, in situations where sufficient data may not be available for more highly differentiated responses. As in the FeelTrace model [5], we distinguish two dimensions to define the affective (or emotional) state: the arousal level—low versus high—and the valence—positive versus negative (Figure 2). A large benefit of a dimensional model is that it enables us to predict more subtle emotions then when we would use a classification in for instance the six basic emotions (happy, sad, surprise, angry, fear, disgust) [7]. Critical affective states are bored (passive/negative) and stressed (active/negative). We expect that we measure underload in the CTL when the user is bored and that we find stress in the ATL when the user is overloaded. The ATL can help disambiguate the CTL and performance outcomes and also indicate critical states when the models do not match at all.

3.1.3 Performance

For the team performance, we will apply "classical" measures for effectiveness and efficiency, and relate them to trust and situation awareness metrics. The performance model will represent which tasks are active (e.g. the tasks the operator is attending to), and the quality of the performance (e.g. time). This model also takes into account factors such as, fatigue and circadian rhythm.

3.1.4 Measures

To identify critical states with the different models, the models need input from the context, psychophysiology, and behavior sensing.

Context

The application can use information from the context as input for the models. Context information can be divided into information about the user, about the environment/situation, and about the domain knowledge of the application. Information about the user can be a user model, the task the user has, and the social role the user has. Environment information is the knowledge of where for example fires are, while domain knowledge is that people in a disaster area have a high chance on being stressed.

Psychophysiology

The physiology can give information about the arousal and valence of the user. Rani [24] uses cardiac response, electrodermal response and electromyographic response to detect anxiety levels. These responses qualify anxiety reasonably well. The muscles in the face also give information about the physical and mental workload of the user. Metaxas [17] describes a method to recognize stress from the face. They use Hidden Markov Models for this purpose, but recognition from the face is difficult due to varying light conditions. Another option is to recognize valence and arousal from the voice, stress for example is the variation in prosodic emphasis [8; 22; 23; 26; 27; 29]. To be dependable the voice has to be monitored over a longer period of time. Several features, such as mean pitch, spectral entropy, jitter, vowel length, can be analyzed with, for instance, different Hidden Markov Models [8] to measure valence and arousal. By measuring the valence and arousal multimodal the recognition is more robust and better. A drawback of all the options we mentioned is that none of them has ever been used outdoors or while users were physically active. In certain work environments such as USAR users will be both.

Behavior sensing

People give a lot of information about their state by their behavior. They change the way they walk and speak. From straight up they can go to a crouching position or change their dialogue from elaborate to to the point. But also the effectiveness, efficiency, and situation awareness give information about the state of the user such as fatigue. In an USAR scenario for instance the effectiveness of a user is low when he/she does not find victims or finds victims in a time consuming manner (efficiency). Questionnaires are used in sensing behavior such as, stress or cognitive load, in the field [2; 9]. A drawback of the use of questionnaires in the USAR area is that there is no time for filling out questionnaires and the assessment of user state should be real time.

4. Discussion and Future Work

In this paper we suggested how critical state recognition can improve the team performance by both enhancing the planning before and during a (search) action. Search areas can be dynamically distributed, the level of information sharing can be adapted, and team members can decide to help a team member for whom a critical state is recognized. As a result team task load can decrease, the shared mental model can improve, and the performance can increase. We presented a critical state recognition method that uses three models; cognitive task load, affective task load, and performance. It is technically possible to implement all three models. The next step is to validate the critical state recognition models in experiments. At the moment we think of evaluation within a gaming simulation.

5. REFERENCES

[1] Al'Absi, M., Hugdahl, K., & Lovallo, W. R. (2002). Adrenocortical stress responses and altered working memory performance. Psychophysiology, 39, 95-99.

[2] Boyd, J. E., Kanas, N., Gushin, V. I., & Saylor, S. (2007). Cultural differences in patterns of mood states on board the International Space Station. Acta Astronautica.

[3] Carver, S., Kingston, R., & Turton, I. (1998). Accessing GIS over the Web: an aid to Public Participation in Environmental Decision-Making. 98, GISRUK, pp. 98-3.

[4] Convertino, G., Ganoe, C. H., Schafer, W. A., Yost, B., & Carroll, J. M. (2005). A Multiple View Approach to Support Common Ground in Distributed and Synchronous Geo-Collaboration. Proceedings of the Third International Conference on Coordinated and Multiple Views in Exploratory Visualization, 2005 (CMV 2005)., 121-132.

[5] Cowie, R., Douglas-Cowie, E., Savvidou, S., McMahon, E., Sawey, M., & Schröder, M. (2000). FEELTRACE: An Instrument for Recording Perceived Emotion in Real Time. Proceedings of the ISCA Workshop on Speech and Emotion, 19-24.

[6] Damasio, A. R. (1995). Descartes'error. New York, NY: Avon Books New York.

[7] Ekman, P. (1992). An argument for basic emotions. Cognition and emotion, 6, 169-200.

[8] Fernandez, R. & Picard, R. (2003). Modeling Drivers' Speech Under Stress. Speech communication, 40, 145-159.

[9] Flynn, C., Eksuzian, D., Vander Ark, S., & Sipes, W. (2002). Spaceflight cognitive assessment tool for the Lunar-Mars Life Support Test Project Phase III Test. In Isolation: NASA Experiments in Closed-Environment Living (104 ed., pp. 155-163).

[10] Grootjen, M., Bierman, E. P. B., & Neerincx, M. A. (2006). Optimizing cognitive task load in naval ship control centres: Design of an adaptive interface. IEA 16th World Congress on Ergonomics.

[11] Grootjen, M., Neerincx, M. A., & Veltman, J. A. (2006). Cognitive task load in a naval ship control centre: from identification to prediction. Ergonomics, 49, 1238-1264.

[12] Hudlicka, E. & McNeese, M. D. (2001). Beyond cognitive engineering: Assessing user affect and belief states to implement adaptive pilot-vehicle interaction. In M.D.McNeese & M. Vidulich (Eds.), Cognitive systems engineering in military aviation environments: Avoiding Cogminutia Fragmentosa. Wright-Patterson Air Force Base, OH: CSERIAC Press.

[13] Looije, R., Te Brake, G., & Neerincx, M. A. (2007). Usability Engineering for Mobile Maps . Mobility conference.

[14] MacEachren, A. M. & Cai, G. (2006). Supporting group work in crisis management: visually mediated humanûGISûhuman dialogue. Environment and Planning B: Planning and Design, 33, 435-456.

[15] MacMillan, J., Paley, M., Entin, E. B., & Elliot, E. E. (2004). Questionnaires for distributed assessment of team mutual awareness. In Handbook of human factors and ergonomics methods.

[16] Mathews, A. & Macleod, C. (1994). Cognitive Approaches to Emotion and Emotional Disorders. Annual Review of Psychology, 45.

[17] Metaxas, D., Venkataraman, S., & Vogler, C. (2004). Image-Based Stress Recognition Using a Model-Based Dynamic Face Tracking System. Proc.Int.Conf.Computational Science 2004 (ICCS 2004), pp. 813-821.

[18] Muntz, R. R., Barclay, T., Dozier, J., Faloutsos, C., Mac Eachren, A. M., Martin, J. L. et al. (2003). IT Roadmap to a Geospatial Future Washington DC: National Academy of Sciences Press.

[19] Murphy, R. R. (2004). Human-robot interaction in rescue robotics. IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews, 34, 138-153.

[20] Neerincx, M. A. (2003). Cognitive task load analysis: allocating tasks and designing support. In E.Hollnagel (Ed.), Handbook of Cognitive Task Design (pp. 283-305). Lawrence Erlbaum.

[21] Neerincx, M. A. (2007). Modelling Cognitive and Affective Load for the Design of Human-Machine Collaboration. In D.Harris (Ed.), Engineering Psychology and Cognitive Ergonomics, HCII 2007 (LNAI 4562 ed., pp. 568-574). Berlin Heidelberg: Springer-Verlag.

[22] Pentland, A. (2005). Socially aware computation and communication. Trento.

[23] Rahurkar, M. & Hansen, J. H. L. (2003). Frequency Distribution Based Weighted Sub-band Approach for Classification of Emotional/Stressful Content in Speech. Proceedings of the 8th European Conference on Speech Communication and Technology (Geneva, Sept.1--4).

[24] Rani, P., Sarkar, N., & Smith, C. A. (2003). Affect-sensitive human-robot cooperation - Theory and experiments. 2, pp. 2382-2387. Taipei.

[25] Rasmussen, J. (1986). Information Processing and Human-Machine Interaction: An Approach to Cognitive Engineering. Elsevier Science Inc. New York, NY, USA.

[26] Rothkrantz, L. J. M., Wiggers, P., van Wees, J. W. A., & van Vark, R. J. (2004). Voice Stress Analysis. Lecture notes in computer science, 449-456.

[27] Ruzanski, E., Hansen, J. H. L., Meyerhoff, J., Saviolakis, G., & Koenig, M. (2005). Effects of Phoneme Characteristics on TEO Feature-based Automatic Stress Detection in Speech. Proceedings of IEEE international conference on Acoustics, Speech, and Signal Processing.

[28] Sorg, B. A. & Whitney, P. (1992). The effect of trait anxiety and situational stress on working memory capacity. Journal of research in personality, 26, 235-241.

[29] Tolkmitt, F. J. & Scherer, K. R. (1986). Effect of experimentally induced stress on vocal parameters. Journal of Experimental Psychology: Human Perception and Performance, 12, 302-313.

[30] Zajonc, R. B. (1980). Feeling and thinking: Preferences need no inferences. American Psychologist, 35, 151-175.