# Capturing context and mental state of knowledge workers

Saskia Koldijk
Radboud University Nijmegen & TNO
The Netherlands
s.koldijk@cs.ru.nl

Supervisors: Wessel Kraaij and Mark Neerincx

## ABSTRACT

We live in an information society, in which effective and efficient interaction with information is crucial. Knowledge workers often experience stress while working with information, due to information overload and inappropriate interruptions by for example incoming mails. We aim to develop a computer tool that supports knowledge workers during their working day, with the final aim of increasing well-being at work. Therefore the tool should be perfectly adapted to the user's current context and user state to provide appropriate feedback and support for their work. Data from unobtrusive sensors will be interpreted by means of pattern recognition approaches and the recognized information will then be used to base feedback and support upon, which is optimally adapted. The performance of our algorithms for context and user state recognition and the final tool will be evaluated in real-world office settings, as well as its effects on well-being at work. In this paper we present our research plans and methodologies, as well as initial results.

## Categories and Subject Descriptors

H.1.2 [**Models and Principles**]: User/Machine Systems – *human information processing, human factors, software psychology*.

I.5.2 [**Pattern Recognition**]: Design Methodology – *classifier design and evaluation, feature evaluation and selection, pattern analysis.*

H.4.1 [**Information Systems Applications**]: Office Automation – *time management, workflow management*.

## General Terms

Measurement, Algorithms, Experimentation, Human Factors.

## Keywords

Knowledge worker, context, stress, workload, unobtrusive sensing, pattern recognition, personalization.



## 1. INTRODUCTION

We live in an information society, in which effective and efficient interaction with information is crucial. Many people are knowledge workers, whose main job it is to interpret and generate information. Due to their typical working conditions these people often experience stress while working with information [1]. They get overwhelmed by all the available information and often have a fragmented way of working due to inappropriate interruptions, for example by incoming mails with information requests. As a consequence, this way of working can diminish well-being at work, which -for some people- may finally result in burn-out.

In the SWELL project[1], we aim to develop a tool that supports knowledge workers during their work. The final aim is to increase well-being at work. Therefore, the tool should be perfectly adapted to the user's current context and user state to provide appropriate feedback and support for their work. Feedback can create more awareness of, for example, mental workload or stress, and possible underlying causes. By providing support, e.g. presenting useful information just in time, the mental workload and stress can be kept in optimal ranges, ensuring well-being at work. The presented PhD project is coupled to another PhD project about "User centred content filtering"[2].

In general, well-being at work is often approached from an organizational point of view. With questionnaires like the NOVA-WEBA [2], employees are asked to rate various aspects of their work. The results of these questionnaires are then used to re-organize the work. In our research, we want to enable real-time measuring of relevant aspects of well-being at work. This information can then be directly acted upon. Much information about the user can be captured unobtrusively in the office. By interpreting this information, the tool can gain awareness of the user's context and mental state and thus provide feedback and support that is optimally suitable.

Regarding the recognition of context, a user interaction context model was developed by [3], in which they use low level operating system and application events, as well as resources like documents, web-pages and emails for populating this context model. Controlled experiments were performed with 5 predefined tasks, e.g. rather structured tasks like form filling, or planning a journey. In our work we want to focus on tasks as they are performed in real-world office settings. Besides task recognition, other aspects of context, like the physical or social context will

[1] http://www.commit-nl.nl > Smart reasoning systems for well-being at work and at home (SWELL)

[2] Also submitted as DC abstract to IIiX2012 (M. Sappelli)

also be considered, as those are of influence on well-being at work too. Moreover, the mental state of the user, in terms of workload, valance, arousal and finally stress, will be taken into account. Our intent is to provide knowledge workers feedback about their way of working and support during their work in order to improve their well-being. To our knowledge, so far no such system has been made.

Regarding the support of knowledge workers, similar, but still different systems are the SWISH system [4], in which the window relatedness and switching behaviour is used to detect content clusters which can be used as support for task management, or the TaskTracer system [5], in which the user can associate activities with certain tasks in order to easily access records of past activities and restore task contexts. The PAL project, with the subsystems CALO [6] and IRIS [7] is meant to ease the working process of a knowledge worker by presenting contextual suggestions or helping with time and task management. However context recognition is not (yet) applied in these systems. The authors themselves suggest that this would be a welcome addition to identify opportunities were the system could intervene to assist, or to decide when and how to interact with the user.

Our basic underlying framework is depicted in Figure 1. The knowledge worker behaves in a certain way, which can be captured by various sensors. This results in low level sensor data that is stored in a privacy ensuring manner. Pattern recognition approaches will be applied to interpret this data, which yields a representation of the user's context and mental state. This information will then be used to select appropriate feedback and support from a repository of interventions. Based upon this feedback and the provided support the user can adjust his or her behaviour, with the final aim to increase well-being at work. Tuning the interpretation module to the specific user and adapting feedback and support to the users context is of importance. Advancements in the state of the art will be achieved in the areas of multimodal sensor integration, contextual reasoning, activity and task recognition, mental and physical state estimation and user adaptation through learning.

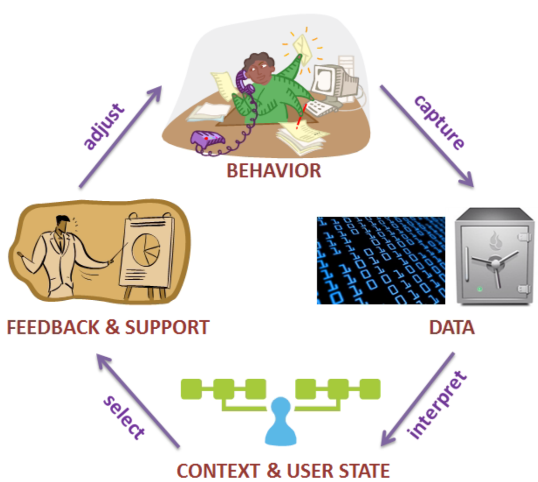


**Figure 1. General framework for providing feedback and support.**

In the remainder of this paper, we will outline our work regarding the following 3 aspects in more detail:

- Requirements for the tool
- Automatic recognition of context and user state
- Developing feedback and support

We describe the research methodologies we use and present some initial results, as well as planned work.

# 2. REQUIREMENTS

The first question to answer is: which aspects need to be considered for making an effective support tool? Literature and user input are used to formulate a set of requirements.

## 2.1 Questionnaire

In order to get insights in the working style and needs of knowledge workers, we developed a questionnaire. In total 47 employees from TNO (Netherlands Organization for Applied Scientific Research) with various backgrounds and different functions responded.

The answers reveal that the knowledge workers spend a great amount of their time (66.7%) at the pc and are very autonomous in managing their working time. They are typically involved in several different projects at a time (avg: 5.3) and have to manage various deadlines, which indicates that good self-management plays an important role. An essential part of the work performed is dependent on other people (mailing, meeting, calling, together 41% of their time). This requires that the work is well planned. Regarding the own work planning, 50% of the knowledge workers indicate to work reactively. This means for many workers the course of actions over a day is not self-determined which might cause a lack of overview or a feeling of stress.

There seems to be no clear preference for working style among knowledge workers. Some prefer to focus on one task whereas others like to switch tasks. Moreover, there are individual differences whether interruptions are perceived as annoying. This is important to know for individualizing the software toward the specific user.

Furthermore, the responses show that recognition on the level of tasks is perceived as more useful than simple application logs. It is important that the system aggregates and interprets low level data and links actions to projects to yield the user useful information. Typical functionality suggested is enabling a comparison of ones activity with the planned activity or the personal average. Most concerns respondents have are about privacy and losing control.

In general the results confirm our view on knowledge workers. The given answers help us to focus our research towards important aspects, like high level interpretation of data and personalization of the tool.

## 2.2 Persona and use cases

A workshop with several knowledge workers and domain experts was organized to formulate personas and use cases to give the problem context more detail and develop possible solutions.

A result of this workshop is a persona at risk of burn-out, for which we worked out personal characteristics, problems experienced and why she is unable to solve these problems herself. Based upon this description we identified underlying causes of the problems experienced, how the person can be helped to solve the problems and how a computer tool can be used for this. Based on our gained information, the next step is to formulate a set of requirements for the tool.

## 3. CONTEXT AND USER STATE

The next question to answer is: is it possible to infer relevant aspects of context and user state, based on unobtrusive sensing? We now describe the underlying models, sensors to be used and the recognized contexts and user states in more detail.

### 3.1 Determinants for well-being at work

We want to develop a computer tool that can help people to better cope with the negative determinants of well-being at work. Preferably it should be possible to capture relevant factors by sensing interactions with a computer. In a literature study we investigated the determinants for well-being at work and decided to focus on the factors of the work itself and the working conditions.

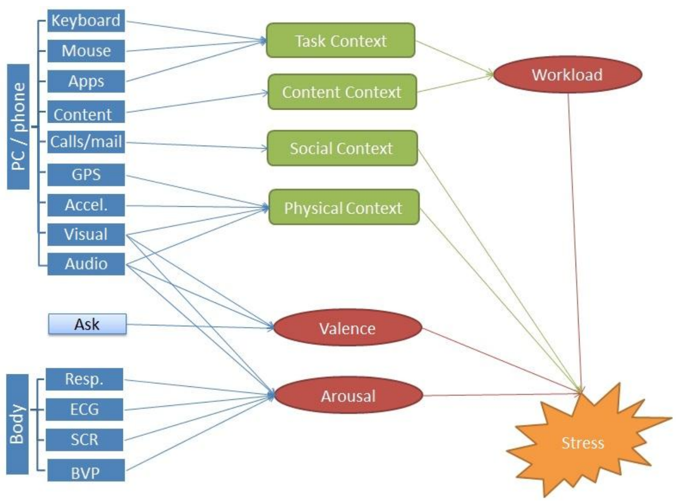


**Figure 2. First setup for linking different sensors to contexts and user states.**

### 3.2 Model of sensors to concepts

In order to automatically recognize the relevant aspects of the user context and the mental state of the user, we take a pattern recognition approach. From sensor data, specific features will be extracted which are provided to a classifier to assign an interpretation label. A first setup for linking different sensors to contexts and user states was made based on a literature study [8].

In Figure 2 you can see that various sensors on the computer can be used for recognizing different aspects of context. The task the user is performing (e.g. writing a report or making a presentation) could be recognized on basis of keyboard, mouse and application information. The content context (e.g. the project worked on) could be determined based upon the accessed content. The social context of the employee could be given by mail and phone conversations. Finally, aspects of the physical context, like location, level of activity, posture or noise level, could be inferred from GPS, accelerometers, visual and audio information.

The combination of tasks and contents worked on can give insights in the mental workload. In combination with the social and physical context this can be used for an estimate of stress.

The emotional state, in terms of valence and arousal, could be estimated based on video or audio, or using additional body sensors measuring respiration, heart signal (ECG), skin response (SCR) or blood volume pulse (BVP). These valence and arousal estimates can give additional information on the experienced stress level. Furthermore, useful information for the model could be gained by asking the user for input, for example asking whether he is in a good or bad mood.

Ideally the final system can monitor the user state in an unobtrusive way. Therefore we hope to find correlations between the rather obtrusive physiological measures and unobtrusive measures, as for example typing behaviour, application usage or posture, so we can use these measures instead in the final application.

As mentioned, this is a first setup which we will need to adapt and extend, based on new insights gained.

### 3.3 User model

The model described in the previous section will be used as basis for every user. Nevertheless it is important to note that each person is different and thus the relations between the different aspects may vary per user. The same task can for example have a lower or higher workload for a knowledge worker depending on his level of experience and expertise. Also well-being is subjective, and so personal characteristics are important to consider.

Therefore a user model will be learned for each user. Steps to take are selecting relevant characteristics to store and how to acquire them. First of all, we think of storing stable personal characteristics, like age, gender and personality characteristics based on an initial questionnaire. Moreover, we will have to store baseline values and averages for each specific user as reference for interpreting behaviour. Finally, we intend to store inferred characteristics in the user model, like the topics of interest or interaction preferences of the user.

### 3.4 Data collection

In order to train and test our recognition models, data from several knowledge workers needs to be collected during their working day and annotated with context labels.

First experiences with collecting data in real-world office settings shows that colleagues are willing to participate in the data collection process, but that annotations require much effort and motivation. Giving participants something in return seemed to be a good approach, for example providing overviews of recognized activities or embedding data collection in a game.

Currently a database to collect large amounts of sensor data is set up. The next step is preparing a good set of annotation labels, implementing a user friendly data collection tool and collecting data from knowledge workers.

### 3.5 Context recognition

Regarding the recognition of the different context aspects, first results for the recognition of tasks have been obtained already [9]. Our research has shown that task recognition on the basis of computer activity (i.e. application usage and mouse and keyboard activity) is challenging but feasible. Unlike other research, in which clearly structured tasks were modelled [10], we showed that task recognition also works for less structured tasks and more spontaneous activity, since our results were obtained using realistic data.

It turned out that task recognition is very personal, as different users have different work styles and task mixes. Nevertheless, we saw that on an individual basis, the simple classifiers we used (KStar, Decision Tree, Naïve Bayes, Multi-layered Perceptron) learn to recognize tasks quite fast, yielding a performance up to 80% which is reasonable high, considering 12 possible task labels that were used.

Finally we concluded, since different users show different patterns of behaviour when performing a task, the classification model should be trained for each specific user to yield optimal task recognition. No more than 2.5 hours (30 instances) of representative training examples are required to train a good model.

These results are very promising. Next, we will address the recognition of other aspects of context, like content involved in and the physical context. We will define these contexts in greater detail and select the most useful sensors and features. Again, the recognition performance and learning speed of several recognition approaches will be tested on real-world data.

### 3.6 User state recognition

Besides recognizing the context, we want to estimate the user state in terms of workload, valence, arousal and finally stress. Therefore, we will have to reason about contexts and user states on a higher level and validate our estimates. Preferably the rather obtrusive body sensors will only be used in our experiments. We hope to find unobtrusive measurements that are correlated with these measures of stress to be used in the final application.

## 4. FEEDBACK AND SUPPORT

The final question to be answered is: which methods of feedback and support are most effective for the user? We organized a workshop with several knowledge workers to collect some ideas.

### 4.1 Possibilities for feedback

To investigate ways for providing insight in the user's context and state, we asked the participants to draw some visualization ideas and afterwards we discussed these sketches.

A participant noted that in the first place simple visualizations should be presented that could be quickly grasped, and that a more detailed overview would be useful later. More metaphorical visualizations included using a traffic light, smiley's or flowers to depict how well the state of working is. More technical visualizations with facts in detail include bar charts and graphics depicting trends over time. The specific visualization preferences turned out to be very different among people, thus personalization is a very important issue.

As next step, various forms of visualization will be created based upon this input, and tested in user experiments for preference and usefulness.

### 4.2 Possibilities for support

To investigate ways for providing support, we asked the knowledge workers to think about how to optimally help them during their work.

Answers showed that to improve self-management, the tool should help them gain insights and discover aspects they were unaware of before. It could help to judge in how far the current situation deviates from the desired, for example warning when the stress level rises or when the working pattern deviates and might indicate a bad way of working. The tool could contrast the planned time with the actual time of completion, which can help to make better time estimates and a more realistic planning. Moreover, the tool could give insights in what kind of days or working styles typically lead to a state of high satisfaction and which do not. It was noted that also positive feedback or compliments are important. Professional tips or best practices of others, e.g. on how to diminish stressors, were appreciated.

Mentioned possibilities to intervene were blocking the calendar when the workload becomes too heavy or filtering incoming emails according to their importance. The tool could also protect the user's flow, by blocking disturbing factors. Regarding the change of behaviour, users could formulate goals to reach, for example to work less or empty the inbox regularly, or indicate which activities have priority for them. Users would like to know whether one's own norms are realistic, which could be done by comparing oneself with a benchmark based on other user's data. Also some games to help improving behaviour were suggested, for example a flow meter.

The next steps we will take are developing suitable ways for support based upon these initial ideas and literature on behaviour change and coping with stress. These will then be tested in user experiments for their appropriateness.

### 4.3 Learning of suitable methods

Every user is different, so the tool should learn from the behaviour of the user whether the applied strategy works, in order to guarantee long lasting success, without irritating the user. Steps to take are generating a system that applies various support strategies, and learns from explicit and implicit feedback from the user.

### 4.4 Human computer interaction

For long lasting success of the tool also the interaction of the system is of importance. Steps to take are developing one or more user interfaces and testing them for their user friendliness. Special attention should be given to the push and pull of information, i.e. the initiative the user has to take or the system takes. As the tool should provide optimal support, it should not stand in the way of the user by inappropriate interactions. The timing and form of support should be well-timed and adapted to user needs and preferences.

## 5. SUMMARY OF PROGRESS

To sum up our progress made so far, we already started with eliciting requirements from users, which now need to be worked out. Moreover, computer interaction data of knowledge workers was already collected and experiments regarding task recognition were performed. The results were very promising, as simple classifiers learn to recognize 12 different tasks with an accuracy of up to 80% after only 2.5 hours (30 instances) of real-world training data. As next step we will work on the recognition of other aspects of context and user states. The recognition accuracy, as well as the usefulness of various sensors and features will be investigated. Regarding feedback and support, we already collected some ideas in a workshop. In the future these ideas will be worked out and tested for their appropriateness. In general we will pay attention to the personalisation of the tool and the evaluation in real-world settings.

It is important to note that the correct and robust interpretation of low level data in terms of context and user state is essential for an effective support tool. In case no satisfying results regarding automatic recognition can be obtained, smart questions to the user will be used to enrich the information the computer has.

## 6. POINTS FOR DISCUSSION

The following points are relevant for discussion in the context of the IIiX doctoral consortium:

- Methods for data collection in real-world settings and annotation of this data by users. How can data best be collected? How do you motivate users to annotate their data? How are privacy concerns handled? How can a dataset be created that can be publicly shared?
- Automatic recognition of relevant aspects of context and how to represent and use this knowledge. Which aspects of context are recognized in related work? Which sensors/ information is used for that? How is the context represented? How is this knowledge used to improve the system? How are these systems evaluated?
- Learning of a user model and how to represent and apply this knowledge. Which user characteristics are considered in related work? How is this information gained and represented? How does it help to improve the system? How is this evaluated?
- Creating an unobtrusive tool, learning from implicit feedback and supporting the user in a courteous way. How can as much as possible be gained from implicit user interaction data? When should we explicitly ask the user for input? Are users willing to help the system? What motivates users to give input? How should we design the system to be perceived as proving friendly help without annoying? How can the effectiveness of the tool and the user experience be evaluated?
- Implications of rich models of context and user state for information retrieval. How can IR profit from knowledge of the different forms of context? In how far can eg. the recognized content or task help IR? Can IR profit from knowledge of the user state in terms of workload, valence, arousal and stress?

## 7. CONCLUSION

In this paper, we presented our research plans regarding the recognition of context and user state and providing feedback and support based upon this information. Several points for discussion were presented. Our research will finally result in insights for applications that are context and user aware by means of unobtrusive sensing and automatic interpretation of data.

## 8. ACKNOWLEDGMENTS

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