Classifying task switches through psycho-physiological sensors

A Markovian approach with time-varying transition probabilities

[redacted]

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Project Proposal

With the increasing speed of technological communication comes the increasing chance of being unnecessarily interrupted by media. This problem of interruptibility is a big issue in Computer Science. As a result, there has been much research on this subject ([3], [4], [5], [8]). The use of sensors is a common practice in the study of interruptibility. Studies such as [3], [5] and [8] employ software-based sensors, based on the observable interaction with either other software or the environment in general. Studies as [4] employ other creative measures such as audio-recording and self-reports. Eventhough interruptibility has been elaborately discussed through indirect observational methods, there seems to be little understanding of the psycho-physiological processes in the human body that are caused by task switches. This paper tries to lay a bridge between biometric techniques and the problem of interruptibility in computer science. The aim of this paper is to examine whether psycho-physiological sensors can be used to accurately classify the occurences of task switches such that interruptions can be timed at such intervals, with the idea of minimizing unncessary interruptions.

This research would differ from other researches like [3] and [4], because it employs psycho-physiological sensors, opposed to software-based sensors or other observational sensors, such as kinesiology-based or recording-based experiments. By investigating physiological sensors, this research could have a contribution to not only the understanding of human processes between tasks and during task switches, but also the feasibility of tools that can accurately classify such task switches. In specific, I would like to shed light on the following questions:

1. Can we detect the occurrence of task switches by analysing psycho-physiological data?
   (a) How close to a task switch can the psycho-physiological data predict the task switch and with what accuracy?
2. How much psycho-physiological data is needed to accurately classify the task switch?
   (a) Is it possible to give accurate classifications by using individual sensor-data or specific combinations of sensor-data?
   (b) What is the feasibility of a (low-cost) tool that uses a (sub)set of the investigated sensors to classify task switches?

For the statistical analysis, I split the analysis into two different parts. Part 1 tries to investigate Research Question 1 and Part 2 tries to investigate Research Question 2.

Analysis Part 1 - task switch recognition

In order to make valid claims whether it is *possible* to classify task switches, I first need to investigate the individual sensor data. This because I need to make sure that the data is filtered and smoothed as much as possible such that unnecessary noise can be reduced or removed completely. After this is done, I will employ a two-state Markov model with time-varying transition probabilities. I've chosen this approach because the time-varying transition Markov model is based on time-varying probabilities such that nonlinearities (e.g. interpersonal differences) and changes in the underlying data can be modelled as well [1]. The time-varying transition probabilities are extremely important as we cannot assume that the current state of the Markovian process doesn't depend on recent past states. I've illustrated this argument in Figure 1 in the Appendix. From this figure it can be seen that if I were to use a linear two-state regime-switching model such as the *logistic regression model*, I would not be able to use all available data and therefore decrease performance of the classifier.

Analysis Part 2 - individual performance

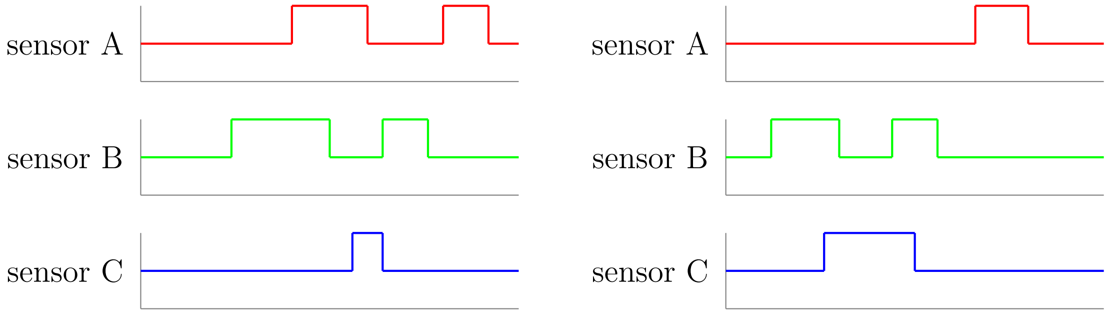
Apart from the general research question, I also want to explore whether task switches can be detected using less sensors, taking into account interpersonal differences, accuracy measures and realtime scenarios. In the second analysis part, the statistical analysis of the data is subdivided into the following consecutive steps. (1) First I will explore the individual properties of the different sensors. The individual data might need to be transformed using various (case-specific) filters[1]. After the exploration of individual properties, I want to (2) examine the performance of the sensors when regressed on the task switch ocurrences individually. For this I plan to use a simple logistic regression model, adjusted for timeseries. Clearly, these individual regressions will yield very specific parameter estimations for each person individually. Therefore, I wish to examine whether there are specific characteristics of the individual sensors, which can be modelled in a more robust manner, such that the estimation method remains robust for interpersonal differences. After establishing an appropriate regime switching estimation for the sensors individually, I will proceed to the last step: (3) using the individual sensor estimations and aggregating the individual signals into a final classifier, that can calculate task switches in realtime with very limited initial learning.

This step differs from *Analysis Part 1* as signals are now processed and assessed *before* they are aggregated. This exploratory research allows me to study how the individual sensors work and to explore intuitive algorithms for aggregating the individual signals in realtime. Also, this approach tries to yield a fresh perspective on out-of-the-box machine learning methods (such as the decision tree), as such methods cannot incorporate nor circumvent the difficulties that interpersonal differences or heteroscedasticity may bring about. The idea of building custom-designed optimizers and case-specific algorithms is a common practice in machine learning and is recommended in many machine learning reviews such as "*A Few Useful Things to Know about Machine Learning*" by Pedro Domingos [2]. By studying the sensors individually, I hope to get a better picture of how a final classifier should work. This knowledge can then, in turn, be used to propose an algorithm that can classify task switches **in realtime**, using a (sub)set of the psycho-physiological sensors that were employed during the experiment.

Hence, my research will consist out of two very distinct parts: (A) verifying the accuracy of classifying task switches, using the employed psycho-physiological sensors from the experiment. (B) Exploring the individual properties of the sensors in order to propose an algorithm (or a tool) that can accurately classify task switches in realtime. ■

[1] `http://en.wikipedia.org/wiki/Smoothing#Smoothing_algorithms`

A Appendix



(a) Illustrative example of a sample I

(b) Illustrative example of a sample II

Figure 1: Visualisation of difficulties when aggregating individual sensor signals

In Figure 1a, the machine learning algorithms that ignore time-dependency might only use the data of sensor *A* and *B*, because they fire simultaneously. For Figure 1b, these classifiers might only use the data of sensor *B* and *C*. This demonstrates how important the time aspect is for using all available data and how interpersonal differences might be overcome if a classifier is constructed that combines signals in a nonlinear and time-dependent manner.

References

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