Untangling Complexity in Control Process Interactions

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Abstract

In safety critical control domains, such as Air Traffic Management (ATM), a detailed understanding of the complex interactions and workflow of users is essential for improving the design of supporting tools. However, few frameworks account for temporal sequences of actions and levels of cognitive control. In this paper, we discuss how interaction in the control room can be seen as processes formed by a framed sequence of directly and indirectly related events, external events as well as user actions. To untangle this complexity, we propose to combine different analysis approaches, the Joint Control Framework and visual sequence mining, which can complement each other to reveal patterns of interactions within and between the processes and assign meaning to them.

Author Keywords

Process complexity; process interaction; control process; joint control framework; visual sequence mining; human-automation interaction

CCS Concepts

•Human-centered computing → Interaction design process and methods; Human computer interaction (HCI);

Introduction

An understanding of the temporal flow of events and action of users in a situation is key to interaction design. This long-time problem applies particularly to next generation control rooms where operators manage critical processes and where AI-support is likely to manifest. Several theoretical frameworks have been proposed to elucidate such interactions, like Distributed Cognition [4], Situated Cognition [12], The Extended Control Model (ECOM) [3], or the Decision Ladder (DL) [11]. However, these frameworks seldom describe in any greater detail how to treat *micro-level* interactions and temporal flow of events and interactions. Naturally, progress in this field would endow a deeper understanding of what constitutes "interaction", strengthen the design field and provide ways to improve system evaluation.

Today, it is possible to capture rich data of users' interactions in laboratory settings and during simulation exercises. For example, data from simulator studies in air traffic control (ATC) typically include eye and head tracking, screen capture, dialogue, as well as user-induced interaction such as mouse pointer positions and on-screen manipulation of physical objects. Moreover, the simulator provides external state information in terms of sectors, aircraft positions and their flight status. In the real-world as well as in the simulator, interactions and events occur in a *temporal sequence*. Some sequences recur in similar ways, over time, reflecting persisting patterns and regular states. However, sequences play out on different time scales, and belong to different kinds of processes. Some are millisecond transitions of gaze between visual areas in visual scan processes, while others are object movements in transport processes that occur over minutes rather than microseconds. Nevertheless, a core challenge in this research is to go from observable interaction and system behaviour data to an understanding of temporal process control.

In this paper, we explore how temporal analysis of joint control can be achieved by using the Joint Control Framework (JCF) [5] going from interaction data to understanding of control and how that manual analysis could be combined with automated analyses through sequence mining. The paper is structured as follows: (1) introduction of approaches to understanding temporal interaction data, (2) Air Traffic Management (ATM) and a control case is introduced, (3) manual analysis of control processes using the JCF, and (4) exploration of patterns in control process through interactive visual sequence mining. We conclude the paper by discussing how this approach can be extended by use of other methods and other interaction data.

Understanding Temporal Interaction Data

Complex interaction processes can be seen as a *sequence of events*. In the case of ATM tower control, the events comprising the sequence can be positions of moving objects in the controllers field of view; interactions of the controller with the working environment; and attention focus of the controller in terms of eye-gaze fixations to visual areas of interest. Commonly, the analysis of processes is concerned with studying and understanding how the events and control interactions building up the process evolve and influence each other. As such, shorter combinations/sequences of events that exhibit an interesting behaviour can be identified as patterns in the data. This interesting behaviour can be that they appear frequently in the data, that they are recurring in relation to certain situations, or that they are diverging from the expected workflow (outliers). During the analysis process, sequences representing entire processes can be broken up into shorter defined periods of time, *episodes*.

To analyze such data sets, quantitative and qualitative approaches can be used separately or combined. This also applies to the extraction of the data to be analyzed. For instance, if eye gaze data is collected, one approach is to divide a visual area into areas-of-interest and then transform the eye tracking part of the data set into sequences of visual movements [16]. Gaze points can also be clustered using algorithms into areas of attention [8], but the analyst must still assign some meaning to these areas. When dividing into areas of interest, we already start to assign meaning, qualitatively, to this quantitative, object-related data.

When analyzing combinations of events as patterns in complex process, we would need to consider that they are state-dependent. Patterns in this rather raw data set could be found even in non-linear processes [14]. This can for instance be based on similarity of current data points versus patterns of previous points, rather than finding linear correlations between variables. The presence of patterns allows a prediction to be made about the next point (simplex projection). It is also possible to distinguish between random variations in data versus data that is state dependent [13]. Further, analyses of data over time can then be performed e.g. centered around populations (Cross-Lagged Panel Model) or individuals (the Random-Intercept Cross-Lagged Panel Model), for details see [7]. However, regardless of analytical approach, these patterns would nevertheless be close to the data set, e.g. be object-centered (e.g. gaze-point-on; object-that-moves). Further, combining data points into areas of interest or attention, changes the data set by merging smaller points (fixations) into larger points.

All together, this creates analytical complexity. On the one hand, analytical complexity poses a challenge for purely manual analyses (even with the help of dedicated tools), since anything but very short episodes would take much time into account to analyse. On the other hand, this also poses a challenge for purely quantitative models of interactions. Although, it is possible to find meaning even in non-linear interactions using analysis of the raw data sets, a hybrid approach may be more promising than using only a "brute force" analysis of the raw data. This will be outlined and discussed in the remainder of the paper.

Application Area - Air Traffic Management

ATM is a control domain where one can find complex interaction processes. The core value of ATM is to maintain safe and well ordered air traffic. Typically, many processes occur at the same time, each with its own goals and priorities. One aircraft may prioritize being on time while another prioritizes fuel efficiency. This variation of intentions increases process variety. Variations in weather and in performance of aircraft and people in carrying out plans creates further variety. For example, a one-second difference in initiating a turn creates large difference in the resulting path. Many processes occur in real-time and are generally not possible to put on hold, making time a core constraint as control must be process-paced. The processes are often entangled in a network of plans and paths, intersecting, turning, and requesting short-cuts. Each of these object processes are also enmeshed in a system of control processes as they are being observed and guided versus situations in the airspace. In many of these processes, the actors/subjects are humans - Air Traffic Controllers (ATCO) - but they could just as well be automated systems. It is important to note that those systems are not fused into one coherent system, but can be seen as a rather loose network of interdependent sub-systems. The multitude of subjects is another source of complexity of the control processes, as is the fact that not all interactions made by the ATCOs are to control the processes. Sometimes they just un-clutter the interface (e.g. moving aircraft radar labels) or idle-fiddling with the Human-Machine Interface (HMI), thus creating noise in human-interface interactions. For an external observer, the interactions are therefore not always easy to understand.

Joint Control Framework, Notions and Definitions

Process types: External, control, and interface.

Object: What is controlled and interacted *with* in the process.

Subject: The agent controlling and interacting with the objects.

Joints: Points in time when the subject is interacting with the process, three basic types: Perception Points (PP), Decision Points (DP), and Action Points (AP).

An ATM Case

In Lundberg et al. [6], episodes with entangled processes from a scenario recorded in an air traffic control tower simulator were analysed with respect to gaze patterns and (lack of) automation in an ATM system. The analyses were made by manually analyzing the raw data, identifying and mapping interactions and gaze patterns recorded with eye tracking glasses. The result was tables of interactions/events and gaze distribution among areas of interest. In the following, we will look into one these episodes to form a basis for discussion. The main process for the ATCO was to control a departing aircraft (DLH4YJ) affected by the entangled processes of controlling two other aircraft, one departing aircraft (NTJ228G), and an aircraft (SEMBJ) flying over the airport. NTJ228G affected the main process by causing a runway incursion (entering the runway without permission) and SEMBJ by drawing attention from the critical situation when calling up on the radio at the same time. The ATCO detected the runway incursion in the last second and stopped the aircraft about to take-off (DLH4YJ).

Analytical Approaches

With the presented ATM case as starting point, we will now exemplify a qualitative and a quantitative approach to tackle the challenges of analyzing, complex, temporal interaction data. The former is based on using the JCF framework and the latter on an interactive sequence mining approach.

Modelling with the Joint Control Framework

The Joint Control Framework [5] was selected as a qualitative approach. It shares properties with other frameworks like the Extended Control Model (ECOM) [3], or the Decision Ladder (DL) [11] with respect to interaction levels. However, JCF also includes a notation for temporal analysis of interactions (see Fig. 1).

The JCF characterises control relations as consisting of subject(s) (the controller) and object(s) (the controlled) - joints. There can be many types of joints, but three that recur in literature are the perception joint, action joint, and decision joint [5]. These are also central in circular/cybernetic models of activity, such as the action "gulfs" in Cognitive Engineering [10], the Contextual Control Model [3], or the basic Perceptual Cycle [9]. Placing these joints on timelines, between subjects and objects creates points in time: Perception Points (PP), Decision Points (DP), and Action Points (AP). Data points such as eye tracking converted to areas of interest, interface action logs, usually describe the object level (e.g. using levers, buttons, or some other physical means). This analysis concerns the meaning of the interactions, with regard to the process being controlled.

Perception, decisions, and actions can take place at six different Levels of Cognitive Control (LACC) from setting high level frames of what goes on (Level 6, Frames) to physical object status or actions (Level 1, Physical) (see [5] for details). This analysis thus concerns the meaning of the interactions, with regard to the process being controlled. For example, is it an interaction regarding generic plans that can recur over time and place (Level 3, Generic), or does it concern implementation constraints such as the length of the runway (Level 2, Implementation)? Or does it refer to an interaction concerning trade-offs between conflicting goals (Level 4, Values), or that appraises the degree of achieving various effect goals (Level 5, Effects)?

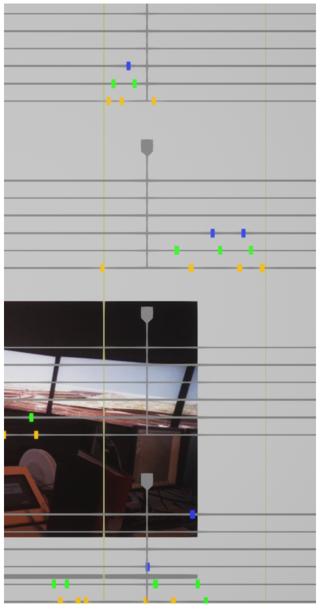

Figure 2: The same score as in Fig.1 but with added AP, blue dots. These AP where not explicitly present in the data set and therefore left out in the first round of analysis. In three of the scores, patterns of DP, AP, and PP can be seen - a decision is made (DP), the action is carried out (AP), and the action is then confirmed (PP).

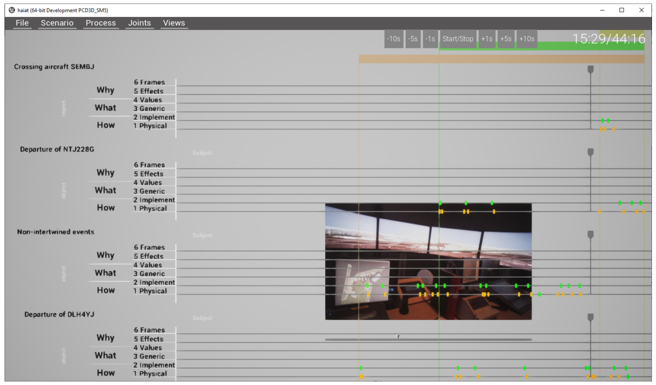

Figure 1: JCF scores. The processes are represented in one six-line score each. Each line in the scores represent a LACC level, level 1 to 6 from bottom up, and the horizontal axis represents time. The analyzed video recording is shown in the background. Joints are represented by orange and green dots on the lines (PP and AP respectively), their vertical and horizontal positions represent LACC level and time respectively.

JCF Analysis of the runway incursion scenario

The original analysis of the runway incursion episode [6] was remodelled using the JCF. In JCF, *scores* are used to display parallel-related processes. Each score consists of six parallel lines, each corresponding to one of the LACC levels. Fig.1 shows the JCF score notation with four different scores. The three processes directly involved in the episode were modelled in one score each (top, second, fourth). The entangling processes (the crossing aircraft and the aircraft causing the runway incursion) are shown in the two upper scores. The main process of the departing DKH4YJ is the bottom score. The second score from the bottom represent all events in other processes not directly affecting the main process. They do however give a richer picture of the overall work context. Green and orange dots represent PP and AP respectively. DPs are not included as they were not explicitly present in the data set. The dots' horizontal position corresponds to the LACC where the interaction with the *process* occurs. All scores are aligned in time. Note that events in the main process (lowest score) and the entangling processes (two top scores) occur very close in time at the end of the scores, which is when the runway incursion takes place.

Fig. 2 shows how the JCF score could look like with tentative positions of DPs (blue) added. The bottom score (departing DLH4YJ process) has two DPs. The first one occurs when the controller realizes that NTJ228G has entered the runway without permission and that the take-off clearance for DLH4YJ must be cancelled. In this example, we tentatively position it after the PP and next to the AP. It is an immediate response to a situation, no new plan is decided upon. The second DP in the same (bottom) score is a re-framing of the situation reflecting the runway incursion. New plans are made to solve the situation. The first part of the plan is then implemented by giving new clearances (actions, green) for NTJ228G to vacate the runway, shown in the second top score in Fig.2 as two sequences of DP, AP, and a PP. The PP occurs when the confirmation of the action is perceived.

Consequently, we can see how the manual JCF analysis can add meaning to the sequential data by categorizing its parts into APs and PPs and by estimating new DPs. It transforms the data set by dividing points over different scores; by positioning the points (vertically) on the LACC as well as filters the data set by excluding idle fiddling with the HMI or other interface-level actions that are not joints with related external processes.

Interactive Visual Sequence Mining of Processes
Viewing a process as an event-sequence also makes it possible to use algorithmic approaches based on sequential pattern mining for their analysis. Sequential pattern mining is concerned with the identification of sub-sequences of events as patterns, which closely matches the analysis purpose of complex process as previously discussed. Agrawal and Srikant [1], initially introduced the problem of mining sequential patterns in the context of market basket analysis. However, the vast number of systems that produce data which are inherently sequential in nature make the applicability of the approach very broad, leading to a multitude of algorithms aiming at extracting sequential patterns from large complex datasets being available in the literature [2].

A common problem of most traditional data mining algorithms is that they identify long lists of patterns, many of which are uninteresting or irrelevant to the specific user and their analysis task. To reduce the produced results to a manageable size, strict constraints are commonly posed to the algorithms so that only frequent patterns are identified. This, however, is problematic when the focus of the analysis is to understand the particularity of processes where the relationships of interest are not necessarily identified by their frequency of occurrence. Moreover, traditional algorithms commonly operate as a "black box" where the contribution of the analyst/user who will benefit from their results, is limited to adjusting some initial parameters which act as constraints on the algorithms. These facts can impede the usefulness of such algorithms in real world analysis scenarios of complex processes that require flexibility of exploration and where the main focus is not frequency. To overcome these issues Vrotsou and Nordman [15] have proposed an exploratory visual sequence mining approach that enables a user to guide the execution of a pattern-growth algorithm towards directions of interest through a interactive visual interface. The approach gives the user control over the mining process by allowing them to choose which sequence patterns to grow, and dynamically apply local constraints. A *pattern tree* representation is used for visualizing the patterns and interacting with the mining algorithm.

In the context of ATM, the patterns sought are sub-sequences of events during an ATC process that are interesting for some reason. They could, for example, be frequently repeating indicating a common behaviour, they could be deviating from an expected behaviour indicating outliers, or they could be leading up to an unwanted situation indicating a potentially dangerous pattern. As such, the approach proposed by Vrotsou and Nordman [15] lends itself well to the task. The applicability of the approach for identifying and exploring visual scan patterns in tower control scenarios was demonstrated in [16].

Even though there are in ATC not standardized visual scan patterns that all ATCOs should be following, there are certain patterns that are expected in certain ATC scenarios as was discussed by Westin et al. [16]. Having this in mind, the exploratory sequence mining approach of Vrotsou and Nordman can be used in the following way for analysing the specific ATM case scenario introduced previously. The different events taking place in the scenario should be extracted and composed into a single sequence representing the process. An analyst could then explore the unfolding sub-processes in search of interest patterns by selecting and growing different parts of the pattern tree (exploring different patterns). Common visual scan patterns could be for example be sought for and their occurrence in the case scenario could be explored. The most common expected visual scan pattern of an ATCO during the departure of an aircraft is to perform repeated runway scans to ensure that the runway is clear for take-off. The runway scans appear as an uninterrupted sequence of visits to the visual Areas of Interest (AOI) representing the runway. The runway incursion caused by NTJ228G will thus be represented as a broken pattern in the data. Moreover, crucial events could be chosen as a *target event*, for example the event of the ATCO stopping the take-off of DLH4YJ, and the sub-sequences leading up to that event could be explored by mining and exploring patterns leading up to that event.

Discussion and Conclusions

We have addressed a key problem in interaction design for control rooms - to post analyze and understand the temporal flow of events and actions of users in a dynamic situation. Multiple source data sets from complex domains as ATM tend to get very large. These amounts of complex data must be possible to analyze in adequate depth within reasonable time.

We have exemplified, for short episodes with a limited number of data sources, how JCF can be used for untangling different processes and identifying relevant events within them by transforming, enriching and filtering the data as described above. However, when applied on larger data sets, this manual approach may be too time consuming. It also relies heavily on the expertise of the analyst. Sequence mining is better suited for analysing larger data sets and has the ability to reveal interaction patterns, but less can be known about the meaning of the interactions and the context in which they appear. Using the interactive sequence mining approach, the runway incursion above is initially represented merely as a broken pattern, rather than as a runway incursion. Further, JCF divided the situation into four scores; they are not uninterrupted sequences as assumed in the sequence mining approach. This adds to the amount of broken sequences identified. The sequence mining will also include e.g. "fiddling" that is filtered out in JCF.

We envision two ways in which the two approaches could be combined to enable more in-depth process analysis. The combination is concerned with enriching the performed sequence mining analysis with qualitatively extracted event data created through JCF. For example, JCF joints could be imported as events in the sequences in order to add more context and include these in the mined patterns. The second combination is concerned with the application of interactive visual sequence mining to a collection of JCF analyzed episodes. In this setting, the resulting sequences of joints produced by the JCF analysis could be used as input sequences into the sequence mining approach to compare them and identify patterns between them. So, for example, several runway incursion episodes could be initially analyzed in JCF and the produced sequence representations of the process could be then mined for common patterns, in search of similar problem-solving strategies and/or behaviours between ATCOs.

Combining sequence mining and JCF analyses has the potential to provide knowledge of both the interactions from a quantitative perspective and the control processes from a more qualitative perspective. This would require a more advanced interactive approach, to use the JCF transformations, reductions, and enrichment's together with mining of data. Our current research is focusing on just this combination. Furthermore, AI and machine learning approaches, building on results from the sequence mining, could be an additional way forward. Extrapolating that thought could even take us to analyzing the processes in real-time. That is however, one step ahead in our future work.

Acknowledgements

The research was funded by the Swedish Transport Administration and Air Navigation Services of Sweden - projects F-AUTO (TRV 2018/41347) and OVaK (TRV 2020/51335).

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