Using Temporal Patterns (T-Patterns) to Derive Stress Factors of Routine Tasks

Oliver Brdiczka
Palo Alto Research Center (PARC)
3333 Coyote Hill Road
Palo Alto, CA, 94304, USA
oliver@parc.com

Norman Makoto Su
Department of Informatics
University of California, Irvine
normsu@ics.uci.edu

Bo Begole
Palo Alto Research Center (PARC)
3333 Coyote Hill Road
Palo Alto, CA, 94304, USA
bo@parc.com

CHI 2009, April 4-9, 2009, Boston, Massachusetts, USA.

ACM 978-1-60558-247-4/09/04.

Abstract
We describe the use of a statistical technique called T-pattern analysis to derive and characterize the routineness of tasks. T-patterns provide significant advantages over traditional sequence analyses by incorporating time. A T-pattern is characterized by a significant time window (critical interval) that describes the duration of this pattern. Our analysis is based on data collected from shadowing 10 knowledge workers over a total of 29 entire work days. We report on the statistics of detected T-patterns and derived correlations with participant perceptions of workload, autonomy, and productivity.

Keywords
Temporal patterns, T-patterns, routine tasks, stress factors

ACM Classification Keywords
H.1.2 User/Machine Systems: Human factors; H.5.2 User Interfaces: Theory and models

Introduction
We propose the utilization of a statistical technique called T-pattern analysis to derive and characterize the

routineness of tasks. Based on the assumption that constant duration of steps or events is distinctive for a routine tasks, the T-pattern analysis isolates patterns that are significant in their temporal configuration. Applied on observational data from application usage, window position, and email communication of 10 employees, we could show the number and length of detected T-patterns correlate with perceived workload, autonomy, and productivity.

The Temporal Dimension of Routines

One side of routines, its temporal regularity (its rhythm), and how awareness of rhythms can facilitate work has been scrutinized in HCI and CSCW research. Begole et al. [1] point out that work patterns differ across time, location, and day of week. By examining past, recurring work rhythms, one can predict future presence based on current events. One can guess, for example, the amount of time needed for a certain individual to prepare and leave for an appointment, go long in meetings, commute to work, return from lunch and other patterns not captured in an individual's online schedule. Reddy and Dourish [2] conducted ethnography at a hospital to examine how people use work rhythms to accomplish information seeking. For example, rhythms can provide valuable information between nurses and doctors. The regular rotation of doctors at intervals allows nurses to simply wait, rather than waste resources and time when he or she needs to seek a physician. Finally, specific usage of certain mediums such as email [3] have been observed to have rhythms (e.g., at the beginning of the day). However, the analyses that have examined the temporal aspects of routines haven't addressed their psychological or organizational impacts.

Uncovering Temporal Patterns

One of our goals in this paper is to advocate the usage of T-patterns in the analysis of human-computer interaction.

We assume that routine tasks can be characterized by specific recurrent actions that are executed within nearly constant time intervals. In order to detect such patterns, we used a probabilistic temporal pattern detection method, called T-pattern detection [4]. T-patterns are recurrent events that occur within a similar temporal configuration (critical interval, CI). The T-pattern detection algorithm uses a statistical test (CI test) that reveals whether the temporal distances between all occurrences of two events are random or not (with respect to a specified p-value). The CI test is based on the null hypothesis that two events A and B are independently and purely randomly (Poisson) distributed over the observation period. The test is applied on all observed temporal distances between the two events A and B and their frequencies, identifying the distances that are supposedly not random according to the specified p-value. Beginning with testing all possible pairs of basic events and thus isolating significant basic patterns, the T-pattern algorithm then successively constructs larger patterns by combining events and significant basic patterns that have been found. Thus, the T-pattern detection algorithm identifies highly significant, hierarchically arranged T-patterns that are composed of statistically related events that repeatedly appear in the same, relatively invariant, temporal configuration.

T-patterns provide significant advantages over traditional sequence analyses by incorporating time. Traditional sequential pattern mining techniques [5] [6] or compression based algorithms (e.g., Lempel-Ziv-Welch) can discover sequential pattern. However, these methods do not take into account the temporal structure of the patterns, as the time delays are not modeled. Markov models [7] are not suitable for this problem either, as the first order Markovian assumption does not hold because patterns are constructed as long ($n > 2$) sequences. In addition, Markov model have problems handling patterns that have very long time intervals.

T-pattern parameters

Our implementation of the T-pattern detection algorithm is based on the description by Magnusson [4]. The relevant parameters used to obtain the results described in this section are:

1. Minimum Occurrence = 2—specifies that a given pattern must occur at least twice to be included in the results.

2. Significance Level = 0.05—specifies the probability that a given pattern would occur in a random (Poisson) distribution of the current data set.

3. Maximum pattern length = 4—specifies the maximum number of action or events that a pattern can be composed of, in order to reduce the complexity of the algorithm and to filter only reasonable pattern sizes.

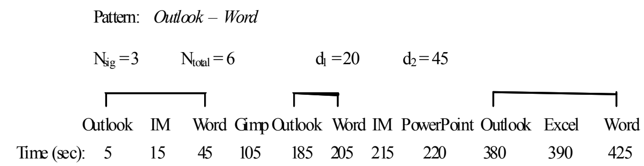

Figure 1. T-pattern analysis detecting a pattern of Word following Outlook from 20 to 45 seconds

Derived T-pattern statistics

The T-pattern detection algorithm identifies a number of T-patterns (N_t) that are significant per task. In addition, the significant minimal and maximal temporal length (d_1 and d_2) for each T-pattern is reported, that is, if A is an earlier and B a later component of the same recurring T-pattern, then, after an occurrence of A at t, there is an interval [t + d_1; t + d_2] ($d_2 > d_1 > 0$) that contains at least one occurrence of B. Figure 1 shows an example case, reporting on the T-pattern Outlook-Word. Based on these T-pattern properties, we can define the following T-pattern statistics:

1. N_t = number of different T-patterns found per task, which refers to the number of T-pattern classes that have been identified to be significant

2. *minL* = $\frac{\sum_{i=1}^{N_t} d_{1i}}{N_t}$ = average minimum temporal length of the T-patterns per task.

Data Collection

Data was collected in situ, shadowing a total of 10 employees. All but one informant (who was shadowed for only two whole days due to scheduling constraints) was shadowed for three whole work days. The observer would meet the informant upon their arrival to work and follow the informant as closely as possible until the end of the business day. Using a paper notepad, the researcher would label, to the second, user tasks and their start/end times. Parallel to the shadowing, logging software has been installed on each participants PC recording application usage. The application usage that has been recorded included application name, window type and size, documents opened, email sender and recipients. Shadowing notes and PC logging data were merged and synchronized. This resulted in a dataset that contained application usage events from the PC logging data that were annotated with their appropriate task label from the shadowing notes.

At the end of each shadowing session, we administered 3 surveys: the NASATLX (Task Load Index) scale [8], a standard survey used to measure stress as a composite of workload, time pressure, effort and frustration; questions adapted from the Job Diagnostic Survey (JDS) [9] and its revised version [10] to measure job autonomy; and questions adapted from the Health and Work Questionnaire (HWQ) to measure worker productivity [11]. Final composite scores of productivity, autonomy, and workload were calculated by simply summing up the individual questions.

Data Analysis and T-pattern statistics correlations

The T-pattern analysis has been conducted separately for the following fields of the logging data trace:

1. Application and window class (appwclass)
2. Application window position (pos)
3. Active Document (doc)
4. Email sender – recipient (email)

Application and window class refers to the current application (e.g. EXCEL.EXE) and the current window class (e.g. ConsoleWindowClass). Note that you normally have several window classes per application, providing a higher granularity observation of the user's actions. The positions of the application windows (x, y, width, height) have been discretized using EM clustering.

	Mean	Std. dev.	Min.	Max.
number clusters	**5.38**	**2.98**	**1**	**14**

Table 1. Mean, standard deviation, minimum and maximum number of window clusters found by EM algorithm from window positions (x, y, width, height)

Table 1 gives summary statistics of the application window position clusters that have been found for the informants. The cluster numbers of the current application window positions are the input events for the T-pattern analysis. Active document refers to the document that the user is currently working on. Email sender and recipient refer to the event when the user receives or selects an email. Sender and recipient ID of this email are the input events of the T-pattern analysis.

		Workload	**Autonomy**	**Productivity**
appw class	N_t	<u>0.33 (0.10)</u>	0.07 (0.73)	0.07 (0.72)
	minL	-0.06 (0.75)	-0.15 (0.47)	-0.16 (0.43)
pos	N_t	0.24 (0.25)	0.09 (0.67)	-0.01 (0.95)
	minL	-0.20 (0.33)	-0.03 (0.88)	-0.15 (0.46)
doc	N	**0.45 (0.04)**	0.35 (0.12)	0.35 (0.12)
	minL	0.13 (0.58)	0.18 (0.43)	0.12 (0.59)
email	N_t	-0.18 (0.39)	0.08 (0.70)	-0.03 (0.87)
	minL	-0.20 (0.33)	<u>-0.34 (0.10)</u>	**-0.48 (0.02)**

Table 2. Pearson's *r* correlations between psychometric and T-pattern statistics

Table 2 reports on some interesting correlations between the T-pattern statistics and the psychometric stress measures. Significant pairs ($p<0.05$) are in bold, while pairs indicating trends ($p<0.10$) are underlined. The corresponding p-values are reported in parenthesis. The number of T-patterns from document usage correlate positively with workload. This relationship indicates that as the number of significant (repetitive) document usage patterns increases, the more the participants felt workload stress. The repetitive switch between documents (and their related content) seems to be particularly stressful. A similar trend can be observed for the application and window class switches. The correlation between application window class and workload is positive, but weaker than for document usage. The minimal length of T-patterns from email sender-recipient is negatively correlated with productivity. From this, we might conclude that the longer the minimal length of sender-recipient patterns, the less the informants felt productive. A similar trend can be found for sender-recipient patterns and autonomy. The correlation is also negative, but less strong than for productivity. Longer repetitive email communication seems to reduce the freedom and efficiency people feel to have in doing their work.

Conclusion

This paper aimed at introducing the T-pattern analysis for detecting temporal patterns in routine tasks. A first correlation analysis of the T-pattern statistics from application usage, window positions and email communication showed that these can be used to indicate workload, autonomy and productivity. We believe that T-patterns are a useful tool for uncovering temporal structure in event-based data. T-patterns unveil a window of constant durations between events, which makes them particularly suitable to characterize routine work. The results presented here are a first step in creating applications that provide users with temporal awareness of their own task performance. Future work will therefore concern possible visualizations of patterns and the creation of pattern signatures for specific tasks.

References

[1] J. B. Begole, J.C. Tang, R. B. Smith, and N. Yankelovich. Work rhythms: Analyzing visualizations of awareness histories of distributed groups. In Proc. of CSCW'02. 334–343, 2002.

[2] M. Reddy, and P. Dourish. A finger on the pulse: Temporal rhythms and information seeking in medical work. In Proc. of CSCW'02. ACM, New Orleans, Louisiana, USA, 344–353, 2004.

[3] V. Bellotti, B. Dalal, N. Good, P. Flynn, D.G. Bobrow, and N. Ducheneaut. What a to-do: Studies of task management towards the design of a personal task list manager. In Proc. of CHI'04. ACM, Vienna, Austria, 735–742, 2004.

[4] M. S. Magnusson. Discovering hidden time patterns in behavior: T-patterns and their detection. *Behavior Research Methods, Instruments, & Computers*, 32(1):93–110, 2000.

[5] R. Srikant and R. Agrawal. Mining sequential patterns: Generalizations and performance improvements. Proc. of the Fifth Int'l Conference on Extending Database Technology (EDBT), pages 3–17, 1996.

[6] J. Pei, J. Han, B. Mortazavi-Asl, H. Pinto, Q. Chen, U. Dayal, and M.-C. Hsu. Prefixspan: mining sequential patterns efficiently by prefix-projected pattern growth. In Proceedings of 17th International Conference on Data Engineering, pages 215-224, 2001.

[7] L.R. Rabiner. A tutorial on hidden Markov models and selected applications in speech recognition. In Proceedings of the IEEE, number 2, pages 257-286, 1989.

[8] S.G. Hart, and L.E. Staveland. Development of nasa-tlx (task load index): Results of empirical and theoretical research. Human Mental Workload 1, 139–183, 1988.

[9] J.R. Hackman, and G.R. Oldham. The Job Diagnostic Survey: An Instrument for the Diagnosis of Jobs and the Evaluation of Job Redesign Projects. Storming Media, New Haven, CT: Yale University, Department of Administration Science, 1974.

[10] J.R. Idaszak, and F. Drasgow. A revision of the job diagnostic survey: Elimination of a measurement artifact. Journal of Applied Psychology 72, 1, 69–74, 1987.

[11] M.T. Halpern, R. Shikiar, R., A.M. Rentz, and Z.M. Khan. Impact of smoking status on workplace absenteeism and productivity. Tobacco Control 10, 3, 233–238, 2001.