Individual Differences in Adaptive Hypermedia

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Preface

The Workshop on Individual Differences in Adaptive Hypermedia is part of the 3rd International Conference on Adaptive Hypermedia and Adaptive Web-based Systems that was held from August 23 to August 26, 2004, at The Eindhoven University of Technology, The Netherlands.

The Workshop explores how to embrace the various dimensions of individual differences into adaptive hypermedia, and investigates the impacts of individual differences on the design, implementation and use of adaptive hypermedia systems.

Individuals differ in traits such as skills, aptitudes and preferences for processing information, constructing meaning from information and applying it to real-world situations. However, existing applications mainly consider users' preferences based on collecting explicit or implicit information, and emphasise on prior knowledge. As a result, it is still not very clear whether adaptive hypermedia systems can accommodate individual differences effectively, in terms of providing individualised navigation support, delivering personalised content, adapting the presentation or the layout to the needs of the user.

The contributions that are presented here cover various dimensions of individual differences, such as the level of knowledge, spatial abilities, learning styles, cognitive styles, accessibility issues and seek to provide answers to the following questions:

- How adaptive hypermedia can improve accessibilities by providing multi modalities that satisfy users with special needs?
- What design guidelines should be established for development, and what criteria are needed for evaluating adaptive hypermedia that can accommodate individual differences?
- How different dimensions of individual differences can be combined in an adaptive hypermedia system?
- What type of information is needed from user profiles to identify the effects of individual differences on user's preferences?
- What kinds of ontologies are needed for representing individual differences dimensions in the user model and the personalisation engine of adaptive hypermedia systems?
- What are the relationships between individual differences and features of adaptive hypermedia systems?

We hope that the Workshop will contribute to the global research in Adaptive Hypermedia by comprehensively reviewing state-of-the-art adaptive hypermedia approaches that accommodate individual differences, will help integrating individual differences theory into adaptive hypermedia applications, and will give some insight into analytical and architectural aspects of adaptive hypermedia that exploit individual differences for personalisation.

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Discovery of Individual User Navigation Styles

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Abstract. Individual differences have been shown to lead to different navigation styles. In this paper we present a pilot study that aims at finding predictors for users' vulnerability to experience disorientation that can be gathered unobtrusively and in real-time. We identified two navigation styles that we called flimsy navigation and laborious navigation that together predict users' perceived disorientation. Our findings suggest that adaptive navigation support that addresses these navigation styles is a promising means to ease the various problems that are commonly associated with users experiencing disorientation.

1 Introduction

Individual differences, ranging from gender differences through system experience to cognitive styles, significantly influence the way that people navigate through hypermedia systems [5]. Many of these individual user characteristics can be gathered using questionnaires or standardized tests. However, for adaptive hypermedia systems this approach is often undesirable, as it requires time and effort from the users, which might eventually put them off. Moreover, not all user characteristics are stable or easily measurable: as an example, a user's motivation and concentration is most likely to change over time.

For this reason, it makes sense to provide users with adaptive navigation support based on users' navigation styles [8]. With knowledge of the strategies that users follow, it is easier to recognize patterns in their navigation paths that indicate usability problems that need to be solved. A typical usability problem is that users become disoriented, or *lost* in a web site [18], which means that they are unable to keep track of their positions: at some point users might not know where they are, how they came there or where they can go to. Several characteristics of user navigation, most importantly those related to page revisits, have been related to success measures, such as task outcomes and user's perceived disorientation [5][8][11].

In this paper we present the results of a pilot study that was aimed at finding patterns in user navigation that indicate a user's vulnerability to perceive disorientation while working on goal-directed tasks that require a fair amount of navigation to complete them. We were able to extract two navigation styles – which we called *flimsy navigation* and *laborious navigation* - that performed well in predicting the user's perceived disorientation. In the next section we will describe shortly how individual differences influence user navigation. Navigation styles and measures for user navigation are dealt with in the subsequent section. The presentation of the pilot study and its results will be followed with a discussion on the generalizability of the study and the implications for adaptive navigation support.

2 Individual Differences in Web Navigation

There is a vast amount of literature showing and analyzing individual differences involved in web navigation. In [7] it is noticed that novices tend to make use of a linear structure in hypermedia systems, when it is made available, while experts tend to navigate non-linearly. [10] demonstrated that students who had more *domain knowledge* displayed more purposeful navigation and allocated time more variably to different pages. *Spatial ability* is an important determinant of hypermedia navigation performance, as reported in several studies [e.g. 4]; users with low spatial abilities have difficulty in constructing and using a visual mental model of the information space. Students with an internal *locus of control* are reported to be better able to structure their navigation and to take advantage of hypertext learning environments [10].

Research on cognitive mechanisms involved in web navigation gains increasing influence in the HCI community. A cognitive model of web navigation should be able to simulate the navigation behavior of real users, producing the same navigation patterns as actual users would do. Many approaches to user navigation modeling are mostly inspired by the theory on *information foraging* [13]. Information foraging theory assumes that people, when possible, will modify their strategies in order to maximize their information gain. More specifically, users continuously compare the benefits of alternative actions, for example digging further into one information resource versus looking for a different resource. Process models that are based on these theories can analyze or simulate users' actions in terms of their individual evaluations of their expected utility.

3 User Navigation Styles

A related line of research aims at directly modeling the user's navigation behavior in order to provide adaptive navigation support in web applications [8]. A dynamic user navigation model could include:

- *syntactic information* (e.g. which links are followed, what does the navigation graph look like, what is the time that users spent on each page)
- *semantic information* (i.e. what is the meaning of the information that the user encountered during navigation)

- *pragmatic information* (i.e. what is the user using the information for, what are the user's goals and tasks)

In this section we focus on the syntactic information. Our aim is to identify patterns in user navigation that indicate problems associated with disorientation, as experienced by the user. In the first subsection we characterize several user navigation styles. In the second subsection we introduce several measures that can be used to capture these navigation styles.

3.1 Navigation Styles and Page Revisits

User navigation can range from goal-directed task completion to more unstructured browsing and exploration of the availability of information or services [7]. Routine browsing is an integral part of web navigation, nowadays; typically, users have a small collection of favorite sites that they visit very frequently [5]. Several taxonomies of web browsing behavior are presented in the literature. One of the finer grained taxonomies is presented in [15], a white paper that is clearly targeted at the ecommerce community in which seven patterns are categorized, based on session length, average page view times and the amount of revisits during this session.

Within a navigation session, users often return to pages that serve as *navigational hubs*. Extensive use of these hubs is reported to be an effective navigation strategy [11]. When looking for information, users often employ search strategies that are quite similar to graph searching algorithms, such as *depth first*, *breadth first* and *heuristic* search [2].

With knowledge of the type of session that users are involved in, and the navigation styles that they employ during these sessions, it is possible to recognize navigation patterns that might indicate usability problems.

3.2 Measures of User Navigation

User navigation paths can be modeled as graphs, with the vertices representing the pages visited and the edges representing the links followed [8]. Several – mostly graph-theoretic and statistical – methods can be used for analyzing this structure. Typical measures include the total number of pages visited to solve a task, the total time needed to solve a task and the average times spent on single pages [2]. Within the navigation paths, patterns may exist that indicate a user navigation style or problems encountered. In our pilot study we made use of a collection of navigation measures that together describe these patterns. They will be shortly described below. For a more detailed discussion about these measures we refer to [8].

Number of Pages and Revisits

As mentioned before, page revisits are very common in web navigation. By capturing various aspects of page revisitation, we aim to find revisitation *patterns* rather than the *amount* of revisitation. The following measures were taken into account:

- the **path length** is the number of pages that the user has requested during a navigation session, including page requests that involved revisits;

– the **relative amount of revisits** is calculated as the probability that any URL visited is a repeat of a previous visit. We adopted the formula that is suggested by Tauscher and Greenberg [17];
– the **page return rate** indicates the average number of times that a page will be revisited. The return rate is calculated by averaging the number of visits to all pages that have been visited at least twice. A more extensive use of navigation landmarks will most likely lead to a limited set of pages that is visited very frequently;
– **back button usage** indicates the percentage of back button clicks among the navigation actions, including backtracking multiple pages at once using the back button;
– **relative amount of home page visits** is a self-descriptive label. 'Relative' refers to a correction of home page visits based on path length.

View Times

The *average time* that users spend at web pages is reported to be an important indicator for user interest and human factors [16]. Besides the average view time, the *median view time* was also taken into account, as users generally spend only little time on the large majority of pages before selecting a link [3]. The median view time is not affected by the few 'high content' pages that were inspected more carefully, and thus provides a better indicator for the average view time while *browsing*.

Navigation Complexity

Navigation complexity can be defined as 'any form of navigation that is not strictly linear'. Complexity measures are mostly derived from graph theory and used frequently for assessing hypertext and its usage [8]. Typical measures reflect the cyclical structure of the navigation graph and the length of navigation sequences within the graph. Several commonly used complexity measures were taken into account:

– the **number of links followed per page** ('fan degree') [14] represents the ratio between the number of links followed and the number of distinct pages visited;
– the **number of cycles** [14] is calculated as the difference between the number of links followed and the number of pages visited. As the number of cycles grows with the length of the navigation path, it can only be used for a fixed time window;
– the **path density** [14] compares the navigation graph to the corresponding fully connected graph. A higher path density indicates that a user makes use of short navigation sequences and regularly returns to pages visited before;
– **compactness** [11] is a measure similar to path density. It indicates that users follow a 'shallow' search strategy. In contrast to the path density, it compares the average distance between any two pages in the navigation graphs to a theoretical minimum and maximum;
– the **average connected distance** [3] indicates the average length of a path between any two connected pages in the navigation graph. A higher average connected distance indicates that users do not return to a page very soon, but only after having browsed for a while. They also return using a link rather than using the back

button. In short, the average connected distance measures the users' confidence in that they 'will find their way back later'.

The navigation measures that are described above are labeled *first-order measures* in this paper, because they are derived directly from the raw data, without taking into account that the measures might be correlated, which most likely would be the case. As an example, the *average connected distance* is calculated independently of *back button usage,* without taking into consideration the fact that usually low values on the former measure are associated with high values on the latter and vice-versa. This aspect was dealt with by calculating *second-order measures* – or *navigation styles*, as will be explained in the next section.

4 Pilot Study – Navigation Styles and Disorientation

In our pilot study we were interested in what navigation styles occur when users perceive disorientation when performing several goal-oriented tasks. In order to better interpret the outcomes, we also collected several user characteristics – as introduced in section two – as well as users' evaluation of their navigation activities. The experimental setup and the results will be discussed in this section.

4.1 Experimental Setup

The study consisted of individual sessions with thirty subjects, all undergraduate and graduate students from two Dutch universities in the age range 19-28, with an average age of 21.5. Participants were selected randomly out of the student lists of both universities, while making sure that males and females were equally presented.

Each session consisted of three stages:

- collection of data on user characteristics;
- the actual navigation session and collection of navigation data;
- evaluation of the navigation session, including a survey on users' perceived disorientation.

Several user characteristics were collected in the first stage. The characteristics that are relevant in the context of this paper are briefly described below. For more details we refer to [9]. *Spatial ability*, *episodic memory* and *working memory* were measured with computerized cognitive tests provided by the Dutch research institute TNO Human Factors. The users' *internet expertise* is composed of self-reported frequencies of internet use and self-assessed level of knowledge. At the beginning of the navigation session the users rated their affective disposition; users who rated themselves high on the states determined, calm and alert, and low on the states sluggish and blue, were considered to be in an *active mood*. *Locus of control* refers to the users' belief in how they contributed to their own success or failure, which was measured with a 20-item scale.

In the navigation session, subjects were asked to perform various tasks in the field of web-assisted personal finance. This field includes using the web to keep a personal budget, to perform financial transactions and decide to save or invest money. The tasks were designed in such a way that it would require a fair amount of navigation to answer or to solve them [9]. Subjects had thirty minutes in total to solve the tasks. Three web sites were used in this study, two of which are dedicated to personal finance. They provide users with advice and tools – such as planners, calculators and educators – to deal with their financial problems. The third site, an online store, was used as a reference.

After the navigation session, the subjects were asked to evaluate their satisfaction with task completion and the usability of the different web sites used. A survey on perceived lostness [1] was also included in the evaluation session.

4.2 Results

As it is most likely that patterns in the first order navigation measures occur simultaneously, second order navigation measures – linear combinations of the first order measures – were calculated. Principal component analysis with *equamax* rotation on twenty-two navigation measures resulted in four factors that together explained 86% of the variance. We will focus on two factors, which account for 27% and 23%, respectively, after rotation. We labeled them *flimsy navigation* and *laborious navigation*, based on their correlations with first-order measures and user characteristics. It should be noted that these styles do not exclude one another. All correlations mentioned are significant with $p<0.05$.

High scores on the *flimsy navigation style* are associated with:
- small number of pages visited ($r=-0.80$)
- high path density ($r=0.80$)
- high median view time ($r=0.77$)

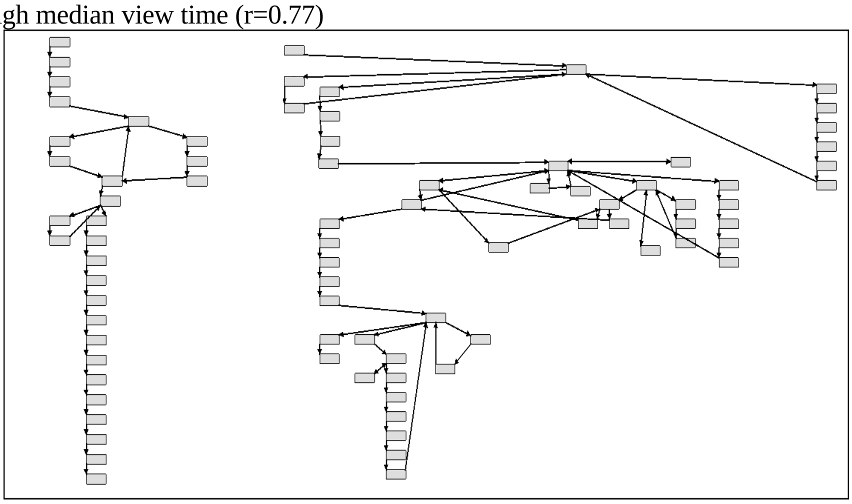

Figure 1. Flimsy (left) versus sturdy (right) navigation. From the figure it can be observed that flimsy navigation is characterized by short navigation paths and a low number of cycles in the navigation graph. The page revisits that did take place in the flimsy navigation path were made using the back button

– short average connected distance (r=-0.70)
– low number of cycles (r=-0.53)
– high rate of home page visiting (r=0.48)
– high frequency of back button use (r=0.39).

Flimsy navigation appeared to be a weak navigation style. Most of the navigation takes place around the site's home page and users regularly return to their starting points. Time is mostly spent on processing content instead of actively locating information. The short average connected distance indicates that users return to a page very soon. Users also prefer to return by using the back button instead of by following links. The low number of cycles indicates that users employing this navigation style do not make extensive use of the means for revisitation available within the sites.

High scores on the flimsy navigation style are associated with low scores on Internet expertise, current active mood, working memory and locus of control. Based on these correlations, it is likely that flimsy navigation is mostly employed by inexperienced users who are not able or not inclined to reconstruct their past actions; rather, they continue along the same path or eventually start over again. For these reasons, we might expect that flimsy navigation is related to users' perceived disorientation.

High scores on the *laborious navigation style* are associated with:
– high number of links followed per page (r=0.95)
– high revisitation rate (r=0.94)
– high number of cycles (r=0.79)
– high return rate (r=0.73)
– high frequency of back button use (r=0.71)
– high path density (r=0.43)
– high number of pages visited (r=0.40)
– short average connected distance (r=-0.39).

This navigation style involves intensive exploration of navigational infrastructure provided by the site. Users seem to employ a trial and error strategy; they follow links merely to see if they are useful or not. They figure out quite fast when paths are not leading towards their goal and return. Revisits are numerous but not redundant: once a page is revisited a different link is followed than before, which constitutes another trial.

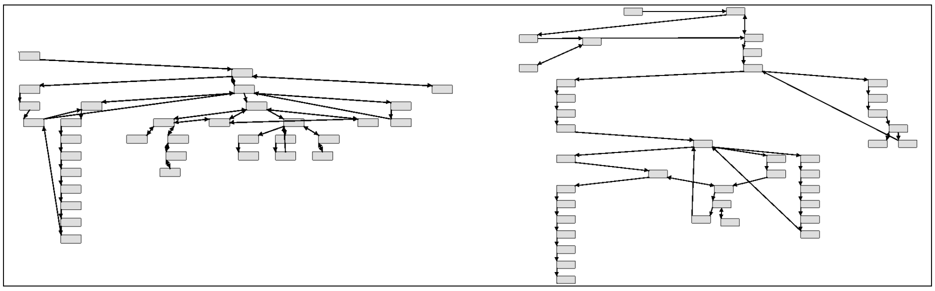

Figure 2. Laborious (left) versus non-laborious (right) navigation. From the figure it can be observed that the laborious navigation style is characterized by a high amount of revisits, with some pages clearly functioning as navigational landmarks.

This behavior is particularly observed on navigational hubs, such as menus and index pages.

High scores on *laborious navigation* are associated with high *episodic memory*, and low *spatial ability*. This style indicates a revisitation pattern that does not lead to disorientation; instead, laborious navigation appears to help users in constructing a conceptual overview of the site structure and then to make use of this model.

Multiple linear regression analysis was used to find out which navigation measures and navigation styles performed best in predicting the subjects' perceived disorientation. Including predictors in regression models was based on the *stepwise method*; the predictive power must be seen as the best one can get with the minimum number of predictors. It turned out that the *flimsy* and *laborious* navigation styles together best predicted the user's perceived disorientation (R^2=0.29) with a large effect size (ES^2 = 0.29/0.71 = 0.41)[1].

Table 1. Prediction of perceived disorientation based on navigation styles. The regression model consists of *perceived disorientation* as dependent variable and *flimsy navigation* and *laborious navigation* as predictors. From the regression coefficients (B) one can observe the positive and negative correlations of flimsy and laborious navigation respectively with perceived disorientation. The standardized coefficients (Beta) show a larger relative importance of flimsy navigation as compared with laborious navigation.

	B	Beta	t	Sig.
(Constant)	40.1		29.66	0.000
Flimsy navigation	3.92	0.46	2.85	0.008
Laborious navigation	-2.38	-0.28	-1.73	0.095

5 Discussion

The results of our pilot study suggest that users' vulnerability to experience disorientation in large web sites can be automatically diagnosed with an attractive level of accuracy. We identified two navigation styles, *flimsy navigation* and *laborious navigation*, which proved to be significant predictors with a large effect size.

The area in which these navigation styles have been identified, is rather limited: they apply to situations where goal-directed and performance-oriented tasks are performed on the web. The domain of web assisted personal finance might seem narrow and this is why we used three different web sites and a relatively complex and heterogeneous range of task. By choosing three different websites to be used in the pilot study, we attempted at randomizing factors pertaining to a specific site structure or interface design. Tasks were not only aiming at locating information but also at

[1] The effect size for regression is calculated with the following formula: $ES^2 = R^2/(1-R^2)$. 0.02 is considered a small effect, 0.15 a medium one and 0.35 a large effect size [6].

using this information to solve actual problems. These decisions were intended to constitute premises for ecological validity and generalizability of the results.

The number of subjects (thirty) was rather limited and relatively homogenous, as they were students. New data is necessary to find out in what situations the identified navigation styles are relevant for predicting disorientation. Most likely, other styles will be identified as well that can explain other facets of disorientation.

5.1 Implications for Adaptive Navigation Support

Prediction of users experiencing disorientation that is based on navigation measures has important practical consequences. From a usability point of view it is useful to identify those users who are at risk of experiencing disorientation and to assist them by adequate, and possibly personalized, navigation support.

Context information is important for effective navigation, as each navigation process is inextricably tied to the structure of the site. Two types of user context can be distinguished: the *structural context* and the *temporal context* [12]. Structural navigation aids – such as site maps, menus and index pages – describe a user's current location and navigation options; temporal navigation aids – such as the browser's back button, bookmarks and visual navigation histories – describe the way that led to this position.

Users that navigate in a *flimsy* manner appear not to be able to reconstruct their navigation paths and therefore are prone to get stuck. Visual navigation histories might help them out. In contrast, users that do not navigate *laboriously* enough and yet do not effectively exploit the site structure, can better be presented local or global site maps or a list of links to index pages. As these types of add-on navigation support typically consume a large amount of screen estate, it is desirable bother users with tools that they do not need.

5.2 Future Perspectives

In this paper we discussed how to address two navigation styles that might indicate or that might lead to users getting disoriented in web sites while working on goal-oriented tasks. The add-on navigation support, as discussed in the previous subsection, aims at improving the way users navigate rather than at forcing users to passively follow some ready-made paths. We believe that this should be the goal of adaptive hypermedia systems in general. Whereas the results of this pilot study might be applicable only in the small domain of web-assisted personal finance, the prospect of adaptive navigation support that fits the user's navigation style is attractive. As an example, users that prefer to extensively explore the sites that they visit, should be supported in doing so, instead of being urged to leave for a different site, unless the system is capable of making clear to the users that the benefit is higher than the cost of altering their strategy.

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References

1. Ahuja, J.S. and Webster, J. Perceived disorientation: an examination of a new measure to assess web design effectiveness. *Interacting with Computers, 14(1)* (2001), 15-29.
2. Berendt, B. and Bernstein, E. Visualizing individual differences in Web navigation: STRATDYN, a tool for analyzing navigation patterns. *Behavior Research Methods, Instruments & Computers 33 (2)* (2001), 243-257.
3. Broder, A., Kumar, R., Farzin, M., Raghaven, P., Rajagopalan, S., Stata, R., Tomkins, A. & Wiener, J. Graph structure in the web. *Proc of 9th WWW Conference* (2000), 247-256.
4. Chen, C. Individual Differences in a Spatial-Semantic Virtual Environment. *Journal of The American Society for Information Science 51 (6)* (2000), 529-542.
5. Chen, S.Y. and Macredie, R.D. Cognitive Styles and Hypermedia Navigation: Development of a Learning Model. *Journal of the American Society for Information Science and Technology 53 (1)* (2002), 3-15
6. Cohen, J. A Power Primer. *Psychological Bulletin 112 (1)* (1992) ,155-159.
7. Eveland, W.P. Jr. and Dunwoody, S. Users and navigation patterns of a science World Wide Web Site for the public. *Public Understanding of Science 7* (1998), 285-311.
8. Herder, E. & Van Dijk, B. Site Structure and User Navigation: Models, Measures and Methods. *In Adaptable and Adaptive Hypermedia Systems (ed. Chen, S.Y. & Magoulas, G.D.)*, to appear.
9. Juvina, I., and Van Oostendorp, H. Individual Differences and Behavioral Aspects Involved in Modeling Web Navigation. *Proc. 8th ERCIM Workshop 'User Interfaces For All'* (2004).
10. MacGregor, S., Hypermedia Navigation Profiles: Cognitive Characteristics and Information Processing Strategies. *Journal of Educational Computing Research 20 (2)* (1999), 189-206.
11. McEneaney, J.E. Graphic and numerical methods to assess navigation in hypertext. *Intl. J. Human-Computer Studies*, 55 (2001), 761-786.
12. Park, J. and Kim, J. Contextual Navigation Aids for Two World Wide Web Systems. *Intl. J. Human-Computer Interaction 12 (2)* (2000), 193-217.
13. Pirolli, P., and Card, S.K. Information foraging. *Psychological Review 105(1)* (1999) 58-82.
14. Rauterberg, M.: A Method of Quantitative Measurement of Cognitive Complexity. *Human-Computer Interaction: Tasks and Organisation* (1992), 295-307.
15. Rozanski, H. D., Bollman G. & Lipman M. Seize the Occasion: Usage-Based Segmentation for Internet Marketers. *eInsights – White Paper*, Booz-Allen & Hamilton (2001)
16. Shahabi, C., Zarkesh, A., Adibi, J. & Shah, V. Knowledge Discovery from Users Web-page Navigation. *Proc. of 7th Int. Workshop on Research Issues in Data Eng. on High Performance Database Management for Large-Scale Applications* (1997).
17. Tauscher, L. & Greenberg, S. How people revisit web pages: empirical findings and implications for the design of history systems. *International Journal of Human-Computer Studies 47* (1997), 97-137.
18. Thüring, M., Hanneman, J. & Haake, J.M. Hypermedia and Cognition: Designing for Comprehension. *Communications of the ACM 38 (8)* (1995), 57-66.