

The Gaze and Mouse Signal as additional Source for User Fingerprints in Browser Applications

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Fig. 1. The data sources for browser fingerprinting.

In this work we inspect different data sources for browser fingerprints. We show which disadvantages and limitations browser statistics have and how this can be avoided with other data sources. Since human visual behavior is a rich source of information and also contains person specific information, it is a valuable source for browser fingerprints. However, human gaze acquisition in the browser also has disadvantages, such as inaccuracies via webcam and the restriction that the user must first allow access to the camera. However, it is also known that the mouse movements and the human gaze correlate and therefore, the mouse movements can be used instead of the gaze signal. In our evaluation we show the influence of all possible combinations of the three information sources for user recognition and describe our simple approach in detail. The data and the Matlab code can be downloaded here <https://atreus.informatik.uni-tuebingen.de/seafiler/d/8e2ab8c3fdd444e1a135/?p=%2FThe%20Gaze%20and%20Mouse%20Signal%20as%20additional%20Source%20...&mode=list>.

CCS Concepts: • **Security and privacy** → **Browser security**; • **General and reference** → *Empirical studies*; • **Information systems** → **Personalization**; • **Computing methodologies** → *Cross-validation*.

Additional Key Words and Phrases: Browser Fingerprint, Fingerprint, Browser Watermarking, Watermarking, Mouse, Gaze, Eye Tracking, Person Reidentification

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1 INTRODUCTION

User identification plays a crucial role in many industrial sectors in which eye tracking [13] did not play a big role so far. In its original form it is used to protect data and access to networks or premises [7, 16, 63]. Today, there is a growing need for user identification, especially in the online environment, which includes both personalized advertising [74] and product placement [12, 72], but also online banking [63] or external access to corporate networks [8]. For security-critical applications such as external access to company networks or online banking, user IDs and passwords have become widely accepted. When using security-critical functionalities, additional security prompts such as a generated PIN or SMS prompts are added. In online advertising, as well as product placement, companies try to identify a person without accessing critical personal data. This is guaranteed in the modern world by so-called cookies [59] since those have to be activated by the user, stateless approaches only use browser statistics [59]. A disadvantage of this method is that the statistics can be used to identify a computer very effectively, but in the case of computers with multiple users all of them are treated as the same person. For the password and user recognition procedure there are also disadvantages. For example if the identification and password is known by an attacker, the attacker can gain access.

In this work we analyze new data sources, like the eye signal and mouse movements. The basic idea is that a person can be identified by means of gaze signals [22] or human visual behavior. This has been shown several times [15, 16, 58]. Since the gaze signal can only be computed with a webcam in a browser, it requires the user to activate and allow the access to the webcam. Additionally, the quality of the camera as well as the different lighting conditions influence the accuracy of the gaze signal [69]. Further scientific work has already been done on the correlation of mouse movements and the human eye signal [57, 64, 68]. It has been found that when clicking or the end point of a mouse movement almost always corresponds to the eye position [57, 64, 68]. With this information, the technique of webcam based eye tracking has changed in that the mouse information is used to calibrate the eye tracker [69]. Another advantage of mouse movements is that this information is freely accessible in the browser and does not have to be activated manually by the user like the camera. We show in this thesis that the mouse information is sufficient to identify a user, which is also scientifically based on the fact that visual behavior is user-specific [15, 16, 58] and that mouse movements in the browser correlate with visual behavior [57, 64, 68].

The application of these data sources in the industrial environment is enormous. For example, it enables continuous user validation for online banking and external access to corporate networks. It would not be enough to have only the password and the user ID, one would also have to be able to emulate the behavior of the correct human user. For user-specific advertising and product placement, it is also possible to differentiate between users on a shared computer and identification of the same user on different computers.

- (1) First work dealing with gaze behavior and mouse movements for a browser based fingerprint. Since browser statistics make it impossible to distinguish between two different users on the same PC, new data sources are needed. We show that this is possible with the visual behavior as well as with the mouse movements.
- (2) Using mouse movements as fingerprints could prove to be very interesting in practice, because this information can be easily retrieved. We show how much information this data source provides and compare it with the webcam based gaze signal and browser statistics. We also show the effectiveness of using combined data sources.

- (3) We compare the traditional browser statistics with new data sources such as the gaze behavior and mouse movements of the user. Since it has already been shown that human visual behavior can be effectively used to identify individuals [15, 16, 58] and mouse movements correlate with visual behavior [57, 64, 68]. Thus it is logical and justifiable why mouse movements can also be effectively used as fingerprints.
- (4) In our evaluation we only use resource-saving machine learning methods [14, 29–32] without validation methods [28, 39] that can be executed even inexpensively in the browser of the user. This extends the field of application of the used data sources as well as the presented simple approach for direct use.

2 RELATED WORK

In this section, we discuss the state of the art regarding browser-based user identification. The first work which has dealt with browser-based user identification is [66]. It analyzed and used statistics about the browser configuration, version and installed extensions. In [10] the approach was proven in a larger study and thus it was shown that the digital fingerprint can be effectively used for user identification via statistics. Further studies [4, 11, 61, 62] dealt with extensions of the statistical features and their quality for user recognition. In [4, 61] an analysis of the stability of the individual characteristics was also carried out. [61, 62] examined different browsers and also analyzed security settings that can prevent fingerprinting. There was also a long term study which dealt with the creation of a unique fingerprint over years [54]. Cross-browser fingerprinting was covered in [6] using both operating system and hardware features. A further extension of these approaches is the use of hashing algorithms to make the calculation and identification more effective [51].

Applications for browser-based fingerprints are described in the literature as user tracking [10, 11], abuse prevention [75], and authentication [4] in many different contexts. For example, security companies use the fingerprint to detect bots or abnormal behavior on web pages [1, 2]. In [75] it is also shown that fingerprinting can be used to easily block scripts that collect data from web pages, but the authors also show that this protection can be easily circumvented. A fingerprint for mobile devices, which was calculated on all hardware and installed software, is described in [5]. This makes it possible to distinguish between the real device and a simulated environment of the same device and thus block network traffic in case of a simulated device.

Literature that deals with abuse prevention is mostly in the context of advertising or e-commerce. This concerns click fraud or credit card payments. Two new inference techniques were presented in [67]. The first technique recognizes click patterns within an advertising network and thus can prevent click fraud. In the second technique, bait clicks are injected and resulting conspicuous patterns are detected. [70] deals with credit card fraud. Here, cheap goods or services are sought that have never been shipped or performed. The authors use different features and machine learning algorithms to detect this type of fraud.

There is also already some work in the field of deep neural networks for fraud detection. In [77] a deep neural network was presented, which analyses the data for similar behaviour. This allows fraud cases, which are repeated and follow the same procedures, to be detected and traced. This technique also helps to protect against known fraud, because the behavior is conspicuous for the system. Several interconnected neural networks have also been used to detect intrusion into computer networks [65]. Here several deep neural networks are used to monitor network communication. These networks detect patterns in the communication which do not correspond to the norm and warn early in case of a possible intrusion. Deep Boltzmann machines were used for fraud detection in biometric systems [9]. For this purpose, features from the deep layers of the network were used, as these have proven to be more robust against attempts of fraud. Another use of deep neural networks for fingerprint calculation is described in [71]. Here, auto-encoders are

used to calculate a hash of a document. Similar documents produce a similar hash. This technique can also be applied to browser statistics to obtain a fingerprint of a user.

While click patterns [67] or drawing symbols [73] have already been used to calculate a fingerprint, we are not aware of any work that deals with mouse movement behavior for the recognition of persons via the web browser. In addition, we use the gaze behavior or the scan path [15, 19] of the test person, which to our knowledge has also not been used for the generation of fingerprints until today. In our work, we compare mouse movements and gaze behavior with conventional browser statistics and also perform analyses regarding combinatorial approaches.

3 METHOD & DATA RECORDING

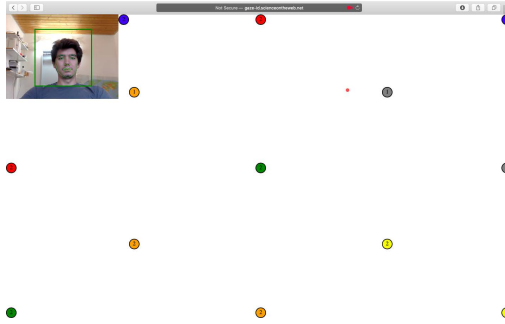


Fig. 2. The initial calibration process. The dots disappear after the subject clicked them with the mouse.

The data was recorded on two PCs with two different browsers each. On each PC, six recordings per person were made, each of which had a minimum length of five minutes and could be of any length. On each computer there were two browsers, each of which was used for three recordings. The choice of websites was limited to six and selected with buttons on the top and bottom of the web page. In addition all sub-pages could be reached as well as other sites could be visited through internal links. This limitation was due to the need of an iframe which allowed us to keep the recording software running constantly. We have also chosen to use a fixed selection of pages that are the same for all subjects, as it is guaranteed that the subjects receive the same stimulus. This reduces the influence of completely different pages on the gaze and mouse data. Before each recording the eye tracker software WebGazer [69] was calibrated. Figure 2 shows our calibration screen. During the calibration the subject had to gaze at each calibration point and click on each point two times. This information was given to WebGazer [69] as calibration coordinates. After the calibration the recording started. In total, six people performed the study, which brings the total number of images to 72 ($2\text{browsers} * 2\text{computers} * 3\text{images} * 6\text{people} = 72$).

The collected data is the eye signal encoded as heatmap, the mouse movements as heatmap and the browser statistics. For the heatmap we have quantized the data into a 10×10 grid, which is valid for both the eye movement [17, 18, 27, 38, 48] and the mouse movement. In addition we normalized the sum of the heatmap to one. The collected browser statistics are standard values like webdriver, webgl, header, language, device memory, etc. according to the FingerprintJS [3]. To store the data online we used a local Apache server [76] with a MySQL database [56], to which the data was sent via Ajax [52] using Javascript [55].

Figure 3 shows the normalized gaze and mouse movement data. Each row corresponds to a separate image. Comparing the mouse and gaze data, a clear difference can be seen where both signals have the main focus relatively central. Since we used an iframe for our recordings, we could

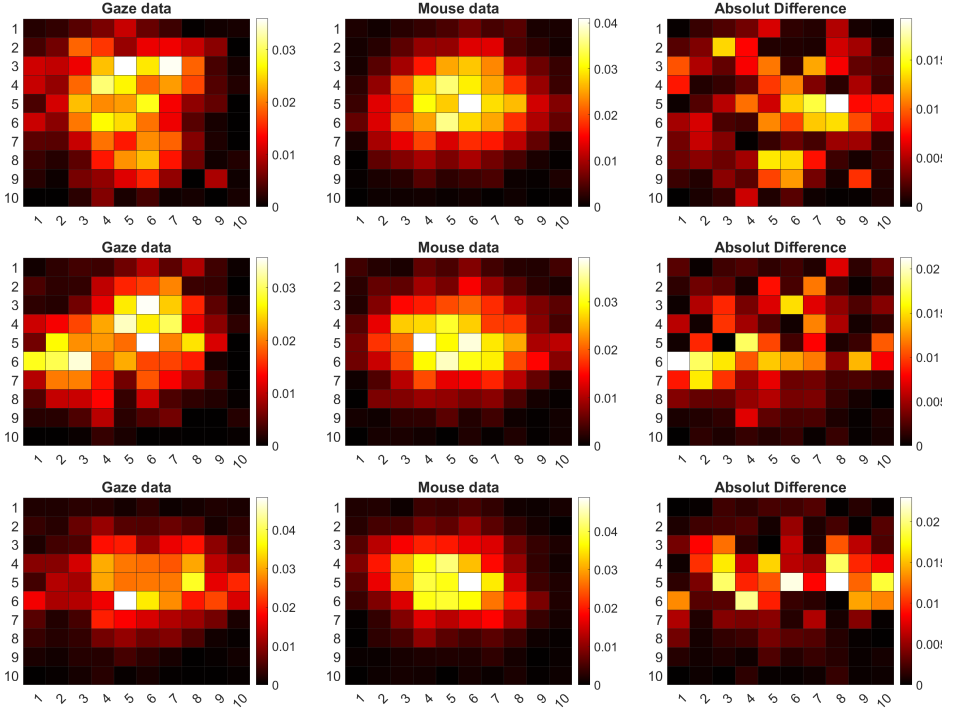


Fig. 3. The gaze, mouse, and absolute difference for three users. Each row corresponds to one subject.

not use tabs in the browser. Scrolling was also done mainly over the mouse wheel and the scrollbar was a bit inside the screen. In the third column in Figure 3, which represents the absolute difference, it can be seen that the signals are clearly different. Nevertheless the signals correlate with each other, which is of course also due to the fact that the heatmap is a quantization and is invariant to time.

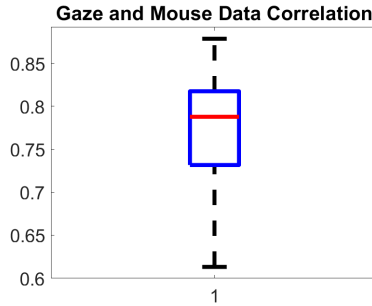


Fig. 4. Correlation between the mouse and the gaze data over all samples as whisker plot.

Figure 4 shows the distribution as a whisker plot of the correlation coefficient over all recorded data between the gaze and mouse signal. The blue box represents the 75% confidence interval and the red line represents the median. Since all values of the correlation coefficient are above 0.5, it can be assumed that there is a very strong relation between the gaze signal and the mouse

4 EVALUATION

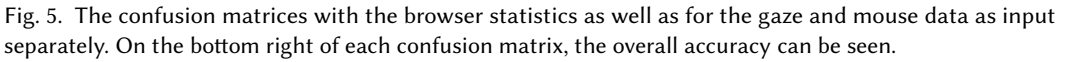


Figure 5 shows the results for the use of the individual data sources (browser statistics, mouse, and gaze) separately. The results are displayed as a confusion matrix to view each class separately. Each confusion matrix also has the overall accuracy in the lower right corner. The matrix on the left side was only evaluated with the browser statistics as input. The overall accuracy is exactly at the chance level (16.66%). This shows that the browser statistics, in the case of computers with multiple users, cannot be used effectively to distinguish between the different users. This is of course logical, because for example two users on the same computer in the same browser have the same statistical values. The middle confusion matrix in Figure 5 shows the results achieved with the mouse heatmap. The overall accuracy of 69.4% is significantly above the chance level of 16.66%. Thus it is clear that the mouse data contains information about the user. Furthermore, this data can be used to distinguish between users who have used the same computer and the same browser. The right matrix in Figure 5 shows the results of the gaze data. These results exceed the results of the mouse data with 80.6% accuracy. This also means that the gaze data can be used to differentiate between users on the same computer and this even better than any other data source.

6

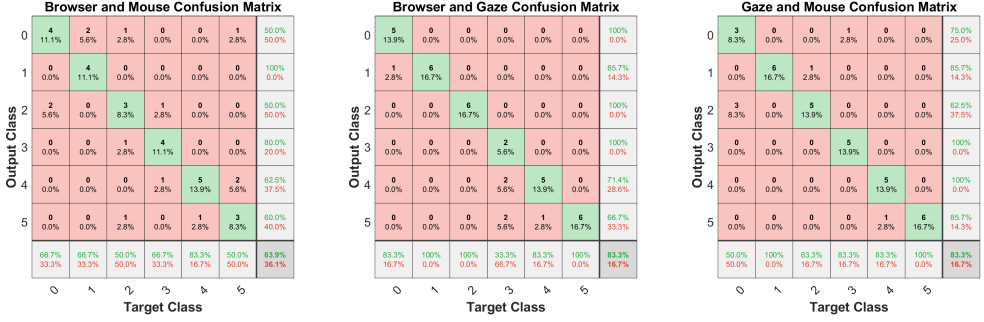


Fig. 6. The confusion matrices for the combinational evaluations. The left most confusion matrix is the browser and mouse data as input. In the central plot the results for the browser and gaze data as input are shown. For the right confusion matrix we combined the gaze and mouse heatmap. On the bottom right of each confusion matrix, the overall accuracy can be seen.

the mouse heatmap. This combination is slightly worse than using the mouse heatmap alone (69.4 to 63.9%). This is mainly due to the fact that in our study the users are equally distributed over all computers and browsers. Normally, that is, that every user has his own computer, except for a few, the browser statistics alone would be very effective and the combination of mouse and browser statistics would be much better. In the middle matrix of Figure 6 the results of the combination of gaze and browser statistics are shown. Here a slight improvement can be seen (80.6% to 83.3%). This is not very much but the same applies as for the combination of mouse and browser statistics. Usually the browser statistics is very effective, because most of the users have their own computer, so this combination would be much more effective. The last and right matrix in Figure 6 shows the results of the mouse and gaze heatmaps. Here is only a small improvement to the gaze heatmaps alone (2.7%). One reason for this is that the two heatmaps have a very similar content and therefore correlate strongly (Figure 4). In addition, larger data volumes of significantly more than six users would have to be included in order to be able to finally evaluate this. In general it can be assumed that this combination is not very effective.

Figure 7 shows the results for the combinatorial use of all data together (browser statistics, mouse, and gaze). As in all previous evaluations, we have used a confusion matrix. The overall result of all data as input is as good as the result when using the gaze data alone (80.6 to 80.6). The individual values of the correct and incorrect classifications in the matrix differ slightly but the overall result shows no improvement. Of course, as for all combinatorial analysis with the browser data, the browser data usually works very well and the result is certainly much better, if there are only a few users which share a computer. Also the combination of the gaze and mouse heatmap may not be optimal, because these data correlate too strongly. However, the gaze heatmap can be replaced with the mouse heatmap. The mouse data have the clear advantage that they can always be retrieved and do not require calibration.

5 CONCLUSION

In this work we have done a small study and analyzed both gaze and mouse data to use them for a digital fingerprint. In our evaluation it is clearly shown that these signals can be used individually as well as in combination for fingerprinting. It also shows that in the case of computers used by multiple users, the browser statistic fails and can no longer distinguish the persons. With our data we can confirm, as in previous work, that the gaze and mouse signals are dependent on each other.

Browser, Gaze, and Mouse Confusion Matrix

0	4 11.1%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
1	0 0.0%	6 16.7%	1 2.8%	0 0.0%	0 0.0%	0 0.0%	85.7% 14.3%
2	2 5.6%	0 0.0%	5 13.9%	0 0.0%	0 0.0%	0 0.0%	71.4% 28.6%
3	0 0.0%	0 0.0%	0 0.0%	4 11.1%	0 0.0%	0 0.0%	100% 0.0%
4	0 0.0%	0 0.0%	0 0.0%	0 0.0%	4 11.1%	0 0.0%	100% 0.0%
5	0 0.0%	0 0.0%	0 0.0%	2 5.6%	2 5.6%	6 16.7%	60.0% 40.0%
	66.7% 33.3%	100% 0.0%	83.3% 16.7%	66.7% 33.3%	66.7% 33.3%	100% 0.0%	80.6% 19.4%
	0	1	2	3	4	5	
	Target Class						

Fig. 7. The confusion matrix with the combination of all data sources which are the browser statistics, the gaze heatmap, and the mouse heatmap. On the bottom right, the overall accuracy can be seen.

The gaze signal scored best in our evaluation to distinguish the users, but it is hardly usable in practice. This is due to the fact that the camera has to be activated by the user and the eye tracker software has to be calibrated in an initial step. This would only be possible in security-critical applications such as online banking, where the customer is willing to protect his account.

The mouse signal is a signal that can always be queried without the user having to allow it. Also, no calibration is necessary and the signal itself is very precise under all external conditions. Since this signal can also be effectively used for digital fingerprinting and works well in the case of multiple users on the same computer, the authors believe that it is highly interesting for real-world applications. The mouse signal can of course be used for many applications in which a person should be recognized. One example is an additional security layer for online banking. If a user's mouse movement data were additionally analyzed and compared by the bank, the misuse of a password and user ID that has become public could be prevented.

A limitation of this work is the small number of test persons in the study. This is due to the current Corona regulations. Therefore, we can only prove a possible effectiveness of the mouse as well as the eye signal, so this work can be considered as proof of concept. Future research in this area should in a first step create a larger study in which significantly more test persons and devices are used.

Further planned improvements are integrating modern pupil detection algorithms [21, 23, 25, 26, 34, 36, 44–47, 49, 50], extracting the information of the eyelids [20, 24, 40–43], and using saliency metrics too [37, 53]. We also want to improve the approach using different visualization techniques for debugging as well as improving the grid based heatmap generation with dynamic AOIs [33, 35, 60].

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