Biometric verification of subjects using saccade eye movements

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Abstract: Biometric verification of subjects as users of computers or other devices has mainly based on fingerprints, face, iris or other images. We developed biometric verification using eye movements to be measured with eye movement videocameras. We measured saccades using the same stimulation for each subject. Our data included signals recorded in two manners: electro-oculographically from 30 subjects and with a videocamera system from additional 30 subjects. Verification tests were run with *k*-means clustering, linear and quadratic discriminant analysis, Naïve Bayes rule and *k* nearest neighbour searching. The highest accuracies were obtained with *k*-means clustering, discriminant analysis and Naïve Bayes rule, up to 90% and even close to 100% at their best.

Keywords: biometric verification; eye movements; saccades; signal analysis; classification; data analysis.

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1 Introduction

Fingerprints and face images are perhaps the most usual biometric means to verify a subject. Numerous computational techniques have been developed for these biometric images, e.g., Chang et al. (2011), Chellappa et al. (2010), Danielyan (2004), Jain et al. (1997), Kant and Nath (2009), Kukharev et al. (2011), Mane and Jadhav (2009), Rani et al. (2008), Shih and Liu (2011), in which the recognition process started from preprocessing and image analysis. Other biometric images have also been studied, for example, iris images (Abdullah et al., 2011; Arivazhagan et al., 2009; Danielyan, 2004; Dey and Samanta, 2010), palmprints (Prasad, 2010) or other images recorded from subjects. In addition, these alternatives have been combined to produce multimodal processes (Mane and Jadhav, 2009) and perhaps to improve verification.

Verification of a user or subject is generally seen as a situation in which the actual user of a computer has to be determined and other possible subjects should be determined as non-users or imposters (Bednarik et al., 2005; Chellappa et al., 2010). Identification is usually seen as a more extensive computational task, in which any individual can be identified and distinguished from others in a group of subjects. We can see the former as a binary classification problem and the latter as a multiclass classification problem. In the present research we describe a novel technique to utilise saccade eye movements for verification purposes, as a simulation to verify an actual user of a computer or some device including a measuring component for eye movements.

Our motivation to develop a verification technique applying eye movements arose from our earlier, long-term research in the field of otoneurological eye movement studies, e.g., Aalto et al. (1989), Juhola et al. (1985, 1997, 2007), Juhola, (1986). Of course, one reason was the technical development over the last 15 years of new videocamera systems to facilitate eye movement studies for various purposes (Morimoto and Mimica, 2005). In addition, we noticed how the values of a few essential features computed from eye movements varied fairly clearly between individuals (Juhola et al., 2007) which formed a sound basis for an objective to exploit eye movements in the process of verifying subjects. As the research of eye movements for human-computer interaction is currently very active, we may assume that in the future such systems can be used to aid interaction with computers in addition to a mouse and keyboard by registering the targets of the user's gaze on a computer screen. Maybe such videocamera systems will be like the webcameras of today, cheap and easy to use. Therefore a verification procedure based on eye movements would be a timely and expedient property for a computer system including eye movement cameras.

Saccades are probably the simplest eye movements (see Figures 1 and 2) to detect with signal analysis (Bahill et al., 1981; Baloh et al., 1976; Juhola et al., 1985, 2007, Juhola, 1986). They are also the fastest eye movements, in fact the fastest movements of any performed by a human being. They are very easy to stimulate. Most of the eye movements performed in daily life are saccades while moving the gaze from one target to another. These properties naturally give additional motivation to design a verification procedure based on saccades and not, for instance, on other eye movement types such as smooth pursuit movements. Using saccades we can deal with short signals of no longer than one to a few minutes being long enough for verification, since they can include tens of saccades. Compared to images this is an advantage because of the decidedly smaller quantities of data, which may reduce the computation times required for verification and simplify the recognition process as such. When eye movement signals are one-dimensional signals, these include much less data than in images.

To the best of our knowledge, one-dimensional physiological signals except voice have so far only seldom been investigated for the purpose of biometric verification or identification (Deshpande and Holambe, 2011). Still, voice is obviously a difficult area, not only because of recognition difficulties of voice signals as such, but since there can be so many disturbing factors such as surrounding noise from several sources, for instance, other speakers and traffic. As to other one-dimensional signals, studies (Chantaf et al., 2010; Israel et al., 2005; Sufi and Khalil, 2011) seem to include virtually only Electrocardiographic (ECG) signals, obviously being the most explored signal type in biomedical engineering. Since any accurate recording of ECG signals always requires a fixed contact to some parts of the limbs or body, its use for rapid verification is complicated. Furthermore, a subject should be at rest, for instance, should not have exerted before a measurement is taken. Otherwise, the intravariation between the ECG signals of an individual might be considerable. Thus these ideas have been perhaps at their best for special purposes, e.g., identifying a patient within a hospital, where ECG signals are recorded from time to time for medical investigations and follow-up. On the other hand, the advantage here is that ECG signal analysis has been studied very extensively for several decades and there are effective computational techniques available in that field.

Eye movements have very rarely been studied for user verification purposes. Recently there have been four attempts to utilise eye movements for verification or identification. In one of these (Nishigaki and Arai, 2008), they detected the blind spot on a subject's retina. If an object of a subject's gaze was displayed at a position outside the blind spot in the visual field of the right user or subject, he or she saw it. In other words, the right subject moved the gaze to it while performing an eye movement. Another subject whose blind spot was very slightly different from that of the correct one should not have seen it, obviously making no saccades during the following one second recorded. The technique seemed to be complicated as every subject had to lean against a chin rest. In addition, there was a possibility that a subject made extraneous eye movements during this 1 s; he might have moved his eyes although did not see the actual object. It is inherent for everyone to constantly shift the gaze while looking at the surroundings – this has perhaps been very important in the distant past in our biological development to survive when human beings were both prey and predators, and, e.g., in traffic at present. During scientific tests extraneous eye movements may be forbidden, but not in natural behaviour expected in the routine use of computers. The investigation included no machine learning algorithm, which was our crucial idea in order to facilitate distinguishing between the right user and others and to adapt to the possible slow intraindividual alteration of a subject's saccades in the course of time.

Secondly, eye movements were studied (Kapczyński et al., 2006; Kasprowski and Ober, 2004) by computing the cepstrum of a signal and by classifying results according to naïve Bayes decision, nearest neighbour searching, decision trees and support vector machines. Thirdly, pupil sizes, gaze velocity and distance between eyes were used (Bednarik et al., 2005) for the biometric objective. Here fast Fourier transform and principal component analysis were computed for eye movement signals. Nearest neighbour searching was applied to the data tested according to the leave-one-out manner. Nevertheless, this technique was chiefly based on using a distance between eyes (images) and eye movements were in a minor role. In any case, their results proposed discriminatory information between subjects in eye movements. Fourthly, a mathematical model of the oculomotor system was used for verification (Komogortsev et al., 2010) focusing on saccade trajectories. The parameter vectors of the model were used as input for the classification to distinguish subjects. Verification was executed by applying nearest neighbour and C4.5 tree classifications.

Figure 1 This includes a 20 s Electro-oculographic (EOG) signal and its stimulation signal, which is the more regular and smoother of these. The stimulation signal precedes the EOG signal, because the subject has followed the stimulation light dot by his gaze, except concerning an extraneous small saccade on the right (starting approximately at sample 7000). Such a saccade was not used as an acceptable case because it was no response to any actual stimulation movement (see online version for colours)

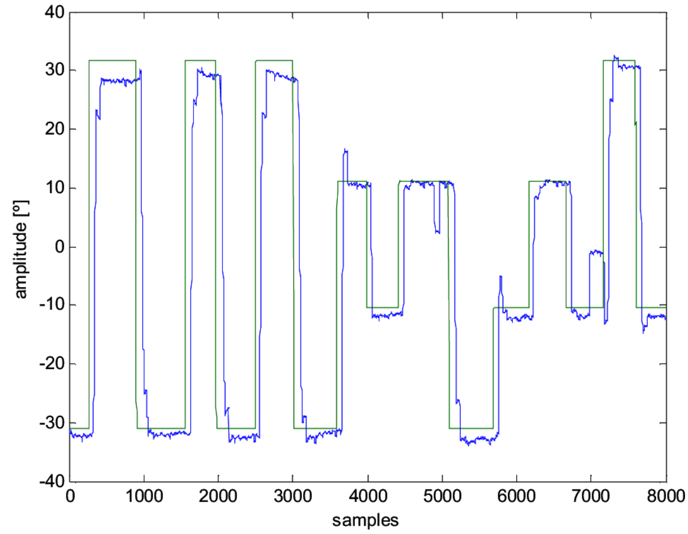
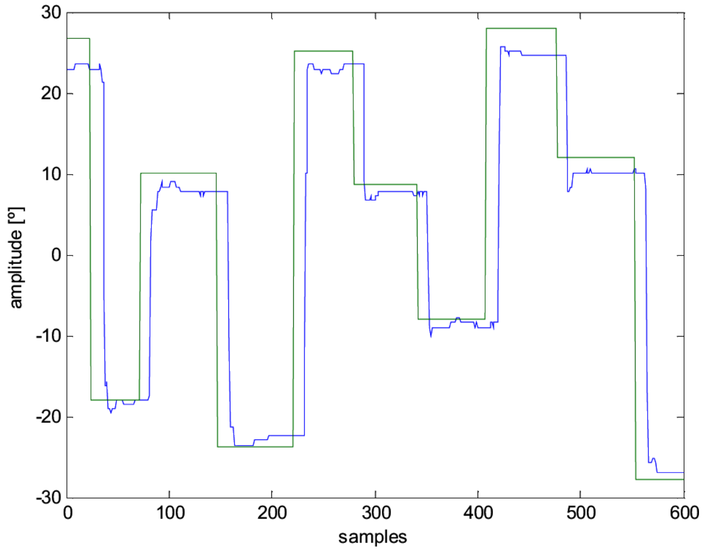


Figure 2 A VOG signal of 20 s and the corresponding smooth stimulation signal (see online version for colours)



2 Recording eye movements

We applied two data sources. The more important data was measured with a videocamera or Video-oculogram (VOG) system (Visual Eyes, Micromedical Technologies, UK). However, since its sampling frequency (frame rate per second) was low, 30 Hz, we used another data set recorded earlier (Juhola et al., 2007). The same stimulation procedure was applied to both, so their results are comparable. The advantage of the latter Electro-oculographic (EOG) data set was that its sampling frequency was as high as 400 Hz. We knew that this might be a critical issue given the earlier research (Andersson et al., 2010; Bahill et al., 1981; Juhola et al., 1985) since, of course, the higher sampling frequency enables gathering more information on eye movement signals.

In VOG there is a videocamera for each eye registering horizontal and vertical eye movements according to positional changes of the pupils in images. In EOG skin electrodes are placed close to the eye corners to register potential differences changing along with the eye movements. To make the stimulation as simple and practical as possible we applied horizontal eye movements only. In addition, EOG is better for horizontal than vertical eye movements, since the latter are sensitive to eye blinks and so wide vertical angles cannot be recorded as accurately as horizontal movements. EOG is typically noisier than VOG, because the former may include abundant noise, such as that originating from facial muscles because of talking, smiling, frowning, gasping etc. Therefore, a subject is advised not to do these during tests. VOG is much more 'user-friendly' in many respects, since it excludes the described problems provided that a subject remembers to keep her eyes open.

Signals such as those in Figures 1 and 2 were measured with the EOG and VOG techniques. The videocamera system worn by an author is seen in Figure 3. With his gaze, he followed a light dot (LEDs) in the black bar in front of him. The light dot was altered rapidly to another place in the bar (actually one LED was switched off and another switched on) so that the angle formed by them in the direction of the spectator seemed to be random from the spectator's viewpoint. Such angles were constant when the distance of the eyes from the bar was constant. However, any slight alteration in this distance would have had only a negligible effect. In addition, varying the time intervals between jumps of the light dot made the stimulation movements random-like for the spectator, although they formed a fixed series of stimulation movements shown for each subject. Such a series was complicated enough so that it could not be learnt although it was repeated several times for an individual. It was important to avoid any proactive saccades that would not have been authentic responses to the stimulation movements arranged. This type of saccade stimulations has been applied to medical investigations for decades as a standard convention, for instance, Aalto et al. (1989), Bahill et al. (1981), Baloh et al. (1976), Kaminiarz et al. (2009). On the other hand, for data analysis it was important that there were several responses to similar stimulations from each subject so that a machine learning algorithm was able to learn the feature values of individuals from the data.

The stimulations employed were used as if in the initialisation of a subject's computer session, which he or she begins by logging into the computer. The idea was not to write a password, but that the computer would recognise its legal user by recording the user's eye movements during the initialisation of the computer system. The purpose was that the computer would present the same stimulation series of light dot jumps on its screen. The user was due to look at the dot jumping approximately once in two seconds for a minute or so. Both stimulation amplitude (lengths of jumps of the light dot) and time intervals between jumps were varied, and most amplitudes should be large enough, such as 40–60°. The large amplitudes guaranteed that variation occurred for saccade features between subjects (Henriksson et al., 1980; Juhola et al., 2007). The large saccade amplitudes were used for verification, but occasionally a smaller one could be interspersed so that the angle was changed surprisingly in the stimulation series to make it random-like for a spectator.

Figure 3 A subject was following the target with his gaze on the bar in front of him. The small red LED was the target light, which jumped abruptly from one place to another along the bar (see online version for colours)

Using both EOG and VOG we utilised data measured from two disjoint sets of individuals each including 30 people. The EOG signals, the duration of which was 80 s, consisted of 12 or more large saccades. Since the VOG signals of duration 64 s included only four large saccades (above 40º), three such segments were measured from each subject. Since the sampling frequency of EOG was 400 Hz and that of VOG 30 Hz only, the VOG signals were linearly interpolated to raise its (artificial) frequency (13 times 30 Hz) up as close as possible to that of EOG in order to enable comparisons between the two techniques and to make VOG 'more accurate' as regards saccade features. The effect of increasing sampling frequencies on saccade features, particularly maximum velocity, was presented earlier (Andersson et al., 2010; Bahill et al., 1981; Juhola et al., 1985). Interpolation, of course, is not the same as an original measurement using a higher sampling frequency, but it can be used as an estimate.

The EOG signals had been recorded monocularly at the same time from both eyes with two skin electrodes and a ground electrode on the forehead. The signals were recorded at 400 Hz, amplified to a scale of ± 10 V, converted with an analog-digital converter of 13 bits and filtered digitally with a lowpass filter of 70 Hz cutoff. Calibration was accomplished with the signals themselves by employing the constant amplitude stimulations of 60º at the beginning and end of each signal. The VOG system included a built-in image processing system to find the pupil of an eye in order to compute eye movements on the basis of the positions of the pupil. The sampling frequency was 30 Hz interpolated up to 390 Hz. The system required no separate calibration (except when the system was installed for the very first time). Since in VOG there were two videocameras, one for each eye, two horizontal signals were received at every measurement. The better one, with less possible noise or artefacts such as eye blinks, was chosen from these two. The amplitude accuracy of both measuring techniques was 1º or better.

The EOG signals had been recorded at a university hospital, and a physician had checked all the voluntary subjects for being able to do the test without any impediments. Spectacles could be used since skin electrodes attached to the corners of the eyes had been used. There had been approximately as many females as males among the 30 subjects and their approximate mean age had been 45 years. The distance between the target of a computer-controlled light dot and a subject had been 1.40 m. The VOG signals were measured from a younger population of 20 males and 10 females, whose mean age was 29 ± 10 years. Since spectacles could not be used in the VOG measurements, the ability of all subjects to see accurately enough was checked first to avoid possible problems such as severe myopia. Associated with the age, two subjects only had presbyopia. In addition, the distance between the target of the bright LED light and a subject was 0.74 m for VOG measurements, shorter than for EOG. There were two different groups: the former (EOG) with ages from young to old and with both sexes equally, and the latter (VOG) as a fairly homogeneous age group of mainly young males. It was hard to find clear indications from the physiological literature showing whether a subject's sex might have any effects on saccades. We have not observed anything like this in our several earlier eye movement studies. Obviously, age can have effects. Therefore, it was interesting to have two quite different groups.

3 Signal analysis and forming data for verification

The EOG eye movement signals were considered according to the method presented, e.g., in Juhola (1986) and Juhola et al. (2007). The VOG eye movement signals, being usually less noisy than EOG, were processed with conventional, straightforward signal analysis methods. The objective in both was to identify saccades from them, i.e., the beginning and end of every saccade as accurately and correctly as possible so that features could be computed from the saccades detected. The principle in both techniques was to approximate the first derivative, which equals the angular velocity of eye movements. Detecting clear, rapid changes in this reveals saccade beginnings and ends. A threshold criterion of 10 s was used for velocity. In addition to this, stimulation signals had to be considered so that we knew at which time each stimulation movement (a jump of the light dot) had started. This was an easy task, because stimulation signals are noiseless and very regular, as seen in Figures 1 and 2.

The EOG data included 12–35 large saccades from each subject. The VOG data consisted of exactly 12 large saccades from a subject. After the detection of saccades the features of latency, amplitude, accuracy and maximum velocity (Figure 4) were computed from every acceptable saccade found from a signal. Latency or reaction time is the time between the beginning of a saccade and its stimulation. An accuracy value is equal to the difference of the amplitudes (angles) of a stimulation movement and its response. A saccade amplitude is more frequently less than its stimulation amplitude, but sometimes also greater. Finally, the maximum of the velocity curve was computed (Figure 4). For the EOG and VOG signals the means and standard deviations of the features are given in Table 1. The negative accuracy denotes smaller saccade amplitudes than stimulation amplitudes. Thus these fairly large standard deviations denoted opportunities to distinguish subjects from each other. The differences of the means between the techniques came from the different subjects and the different measurement techniques.

Table 1 Means and standard deviations of features in the EOG and VOG data sets and their ratios between interindividual variation and intraindividual variation

Data set	*Amplitude* (º)	*Accuracy* (º)	*Latency* (s)	*Maximum velocity* (º/s)	*Duration* (s)	*Maximum acceleration* (º/s^2)	*Maximum deceleration* (º/s^2)
				Means and standard deviations			
EOG	53 ± 11	−7 ± 11	0.231 ± 0.110	631 ± 121			
VOG	47 ± 11	2 ± 8	0.216 ± 0.058	965 ± 280	0.182 ± 0.055	42980 ± 23667	40464 ± 24757
				Ratios r_j of interindividual and intraindividual variations			
EOG	0.81	0.85	1.39	1.33			
VOG	0.97	0.68	0.40	0.71	0.36	0.71	0.75

The features described above are commonly used in medical and physiological tests, because changing in these can reveal peculiarity of a human being's physiology. Further, others are sometimes also computed. We still computed the duration, maximum angular acceleration and maximum angular deceleration (Table 1) of the saccades of the VOG data in order to see whether these could improve the verification results of our main data. The duration is equal to the time difference between the beginning and end of a saccade. The acceleration curve is the approximated second derivative during a saccade (Figure 4). The latter part of this curve consists of deceleration (in the opposite direction in Figure 4). The maxima of both parts form two additional physiologically meaningful features.

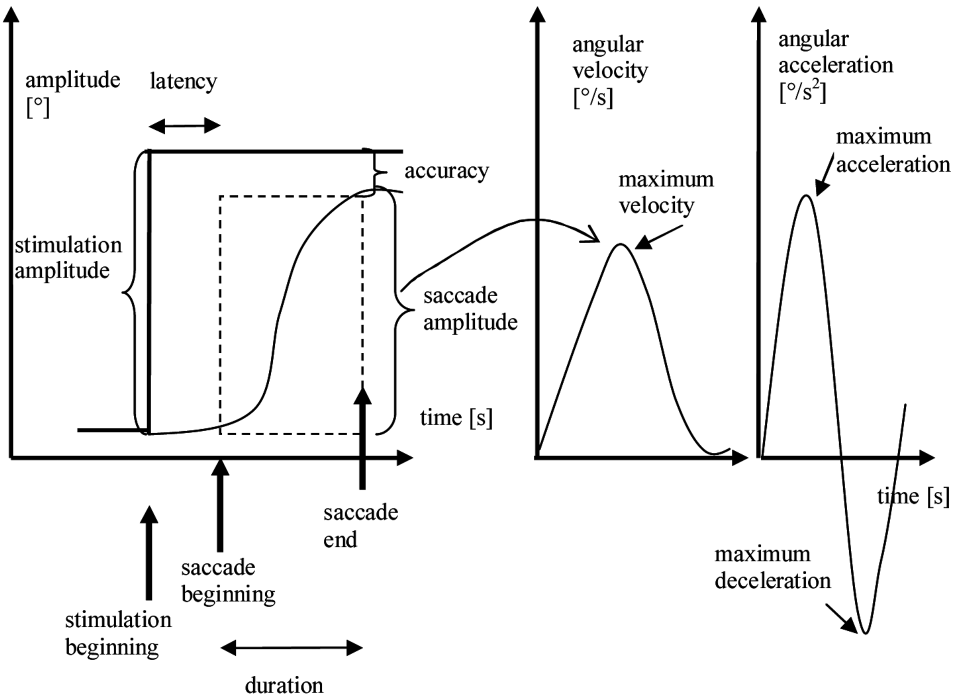
To further explore the separation ability of the features we calculated ratios of interindividual and intraindividual variations in the following (Gu et al., 2003). Here j denotes a feature, n is equal to the number of subjects, $\bar{u}_{ij}$ is equal to the mean of feature j of subject i, $\bar{e}_j$ the mean of feature j for all subjects, u_{kj} the value of feature j of saccade k for subject i and p_i the number of the saccades for subject i. The higher the ratio, the better the distinguishing property of a feature is met:

$$r_j = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\bar{u}_{ij} - \bar{e}_j)^2}}{\frac{1}{n}\sum_{i=1}^{n}\sqrt{\frac{1}{p_i}\sum_{k=1}^{p_i}(u_{kj} - \bar{u}_{ij})^2}}.$$

The results r_j in Table 1 indicated that the features of accuracy, latency and maximum velocities were better to distinguish in EOG than VOG because of their greater values in EOG. Thus these predicted that EOG saccades could be verified better. Perhaps the originally low sampling frequency of VOG also affected this, even after the interpolation, so that the ratios of VOG were less than for EOG, apart from the amplitudes. Nonetheless, we cannot draw any firm conclusions about this, since the two data sets were entirely disjoint, not only measured with the different techniques, but also from different subjects.

We restricted ourselves to the preceding time domain variables, only excluding possible frequency domain variables. This choice was based on the extensive use of these time domain variables in such areas of medicine as physiology, ophthalmology, otoneurology and neurophysiology and medical informatics since the 1960s (Bahill et al., 1981; Baloh et al., 1976; Boghen et al., 1974; Bollen et al., 1993; Henriksson et al., 1980; Juhola et al., 1985, 1997, 2007; Pyykkö et al., 1984; Robinson, 1964; Schmidt et al., 1979; Thomas and O'Beirne, 1967). We therefore knew that the features selected can express various physiological phenomena. As regards verification with eye movements, cepstrum was applied (Kasprowski and Ober, 2006), and fast Fourier transform (spectrum) and principal component analysis were used (Bednarik et al., 2005). Nevertheless, the significance of eye movements was minor in the latter, since the verification computation was chiefly on the basis of the image analysis subject to the distance of eyes and pupil diameters. Naturally, the use of frequency domain is worth studying although not included in the present research.

Figure 4 An ideal saccade curve on the left from which seven features can be computed: amplitude, accuracy, latency, duration, maximum angular velocity, maximum angular acceleration and maximum angular deceleration. All are physiological features used in medical, psychological etc. investigations



4 Verification tests

Two test conditions were applied to simulate the verification of a user on the basis of saccade eye movements. For the first test condition we needed two classes: saccades of the right user and those of others called non-users. For the second test condition we needed a third group of subjects, excluding the right user and non-users used for a training set. The third group then formed a test set of imposters.

Condition 1:

For ii=1,..,t **do** {main loop is repeated for the sake of random selections}
  For i=1,..,n **do** {n equals the number of subjects in the whole set}
    For l=1,..,a **do** {a equals the number of saccades of subject i}
      To form a training set:
      Take other a-1 saccades of a user i other than the lth **and select randomly** b saccades from each of c subjects j (non-user), j=1,…,c, $j≠i$, $c≤n$-1.
      To form a test set:
      Take a user's lth saccade (excluded in training) to be the test saccade.
      Test (classify with method x) and **check** whether either correct or incorrect classification was found.
    End
    The majority of either correct or incorrect classifications decides the verification result for subject i.
  End
  Compute the numbers of correct and incorrect verifications.
End
Compute the means of correct and incorrect verifications for t iterations.

Condition 2:

For ii=1,..,t **do** {main loop is repeated for the sake of random selections}
  For i=1,..,n **do** {n equals the number of subjects in the whole set}
    To form a training set:
    Take a saccades of user i **and select randomly** 2b saccades from each of approximately d=c/2 subjects j (non-user) **randomly selected**, j=1,…,d, $j≠i$, $c≤n$-1.
    For k=d+1,…,c, $k≠i$, $c≤n$-1 **do** {these subjects k are imposters}
      To form a test set:
      Randomly select an imposter's saccade from kth subject to be the test saccade.
      Test (classify with method x) and **check** whether either correct or incorrect classification was found.
    End
    The majority of either correct or incorrect classifications decides the verification result for subject i.
  End
  Compute the numbers of correct and incorrect verifications.
End
Compute the means of correct and incorrect verifications for t iterations.

First, the right user was due to be verified as such in the first condition. The former pseudocode described how a training set and its corresponding test set of one saccade were built for the classification of n subjects. Since the leave-one-out testing method was used, one saccade at a time formed a test set and all other saccades of the same subject (the right user) were a part of a training set jointly with some saccades randomly taken from other subjects (non-users).

For the second condition, we had to divide subjects excluding the right user into non-users and imposters, each of these two groups being approximately equal parts of n–1 subjects. Test saccades were taken from the group of imposters.

The ratio between the number of the saccades of the right user and that of non-users could have been selected in numerous ways, but it was reasonable to set more saccades in the latter, which should represent a clearly larger area in the feature space. We determined two different selections to form these ratios as follows.

For the first selection and for the first condition there, the saccades of every subject as the right user were taken and these were tested against one saccade ($b = 1$) from other $c = 18$ subjects as non-users (not the right user) randomly chosen from 29 subjects. Alternately each of $n = 30$ subjects was in the role of the right user. For the second test condition the saccades of each subject (right user) were taken against $2b = 2$ saccades times some other $d = 9$ subjects (non-users). Additional 9 random subjects were used as imposters due to be verified as such (not the right user). Since there were at least 12 (large amplitude) saccades from each subject, we varied this selection when there were more (only in EOG). Thus, $a = 12$ saccades were taken for the right user. In this way, there were a user's 11 saccades versus non-users' 18 saccades in a training set of the first condition and a user's 12 saccades versus non-users' 18 saccades in that of the second condition.

For the second selection and for its first condition there were again $a = 12$ saccades for the right user. Then $b = 1$ saccade was taken randomly from each of $c = 29$ non-users. In the second condition $2b = 2$ saccades were taken randomly from each of $c = 15$ non-users. Here the saccades of $d = 14$ imposters were naturally used merely for testing, not for training, since in reality they would not have been known in advance. When 10 more or less different training sets had been built, we could run $t = 10$ test rounds for 30 subjects using both EOG and VOG data, i.e., 60 individuals in total. The results were then computed for 300 test series for every classification setup. Thus, there were a user's 11 saccades versus non-users' 29 saccades in a training set of the first condition and a user's 12 saccades versus non-users' 30 saccades in that of the second condition.

Because the number of saccades was rather small, we ran leave-one-out tests for both data sets as described. This is appropriate for small data sets. A test result was checked as to whether it was correct: in the first test condition a saccade of the right user denoting this individual and in the second test condition a saccade of an imposter denoting non-users' saccades. Our verification problem was a binary classification task for both conditions.

If an entire guess had been made for classification in the first condition of the second selection, it would have been incorrect, since the a priori probability of incorrect classification was 29/40, greater than 0.5. Instead, that of the correct classification was 11/40 in every training set. Therefore, no pure guess would have helped here, but a machine learning algorithm really had to learn the features from a data set. Thinking of the situation more abstractly, we can understand that the binary classification task contained a feature space of the current features and values, in which every right user consisted of a minor part and the corresponding non-users the rest, a major part of the feature space used. Imposters were probably within the volume of the feature space, but their feature values were not known in advance as for those of a training set. On the average, imposters ought to resemble more the non-users of a training set than the right user. More similar cases ought to be present among non-users, because non-users predominated in a far larger part of the feature space volume used than that of a single correct user.

We ran our classifications using *k*-means clustering, *k* nearest neighbour searching, linear and quadratic discriminant analysis and naïve Bayes rule. These methods were chosen since they can be trained even with relatively small training sets. They can cope with situations where a class distribution between two classes is rather imbalanced, for instance, 10% and 90% of training cases. (Although we did not test so biased distributions this time, they are in our future plans.) For example, multilayer perceptron networks might be unsuitable due to the reasons presented (Siermala and Juhola, 2006; Autio et al., 2007). Computational time complexities were not crucial here, since the numbers of input data were relatively small, probably not more than a few hundred training cases and fewer test cases. Naturally, there are other classification methods that could be as effective as these tested. For example, support vector machines could be such since they are designed especially for binary classifications, but we shall address other classification methods in our future research.

For clustering we also tested different distance measures and feature values either normalised into interval [0,1] or without normalisation. As seen in the previous means of the features (in Section 3), their scales varied considerably. Thus normalisation might have affected something in machine learning. In addition, to compare EOG and VOG results we ran VOG tests with the basic four features. Furthermore, we tested the VOG data set with all seven features as described above.

5 Test results

As mentioned, 10·30 random test series were executed in the manner of leave-one-out among a set of 30 subjects in both EOG and VOG data. There were two selections for the sizes of the groups of non-users (9 or 15 subjects) and imposters (9 or 14 subjects) and two test conditions for these: correct user verification and imposter verification. All the computation was executed with Matlab R2010a™ (MathWorks Inc., USA). The results are described in the following, first for the first selection and then slightly more concisely for the second selection.

For the first selection we performed tests by using *k*-means clustering either without or with feature value normalisation. We tested four distance measures: Euclidean and city block (Manhattan) in Table 2, and cosine and correlation distance measures in Table 3. (To limit the number of results presented we did not give standard deviations, which were mostly small, a few percent or less.) The numbers of clusters were tested from 2 to 6. Greater numbers of clusters were not applied since there were only 29 (or 30 for the second condition) cases altogether in a training set in our binary classification. We found that greater numbers of clusters would also have started to yield empty clusters. Understandably, this was due to the small number of training cases. For the VOG data, there were two alternatives of the features applied. V4 included amplitude, accuracy, latency and maximum velocity. In addition to these, V7 comprised duration, maximum acceleration and maximum deceleration. The results are given as accuracies in percentages, in other words, how many classifications were correct related to all cases tested. If false rejection rates are desired (Type I error or false negative rate), these are formed by decreasing an accuracy value from 100% in the first condition. Correspondingly, false acceptance rates (Type II error or false positive rate) can be calculated in the second condition.

Looking at the best accuracies in Tables 2 and 3 we found that the results of the EOG data set were better than those of the VOG data set for the condition 1. Instead, for condition 2 there were no such differences. The best accuracies of condition 1 were typically obtained with 5 or 6 clusters. Their differences were small between all clusters for condition 2, except occasionally in 2–4 clusters of EOG. Subject to the best VOG results, condition 2 was better classified than condition 1, but between the best EOG results no differences could be seen.

Table 2 Selection 1: Clustering results in percentages of *k*-means (*k* equal to 2, …, 6) without and with feature value normalisation to [0,1] for Euclidean and city block distance measures. EOG denotes the results of the EOG data set, V4 the VOG data set with four features and V7 with seven features. The best value or values of every column are given in bold face and their mean is *B*

	With normalisation						*Without normalisation*					
	Euclidean distance measure											
	Condition 1			*Condition 2*			*Condition 1*			*Condition 2*		
k	*EOG*	*V4*	*V7*	*EOG*	*V4*	*V7*	*EOG*	*V4*	*V7*	*EOG*	*V4*	*V7*
2	58 ± 6	32 ± 5	25 ± 7	93 ± 5	**97 ± 2**	**98 ± 2**	69 ± 5	15 ± 4	16 ± 5	87 ± 6	**99 ± 2**	98 ± 3
3	88 ± 5	56 ± 8	48 ± 5	88 ± 6	95 ± 4	96 ± 2	84 ± 6	42 ± 8	51 ± 8	96 ± 3	93 ± 5	97 ± 4
4	94 ± 5	69 ± 7	63 ± 7	93 ± 6	96 ± 3	**98 ± 2**	89 ± 5	62 ± 8	63 ± 8	95 ± 4	96 ± 3	96 ± 3
5	**97 ± 3**	79 ± 3	79 ± 6	**98 ± 3**	**97 ± 4**	**98 ± 4**	89 ± 5	75 ± 9	80 ± 6	**98 ± 2**	96 ± 3	**99 ± 2**
6	**97 ± 3**	**83 ± 5**	**83 ± 5**	97 ± 2	**97 ± 2**	**98 ± 2**	**97 ± 2**	**85 ± 11**	84 ± 7	96 ± 4	97 ± 3	98 ± 2
B	*93*						*94*					
	City block distance measure											
	Condition 1			*Condition 2*			*Condition 1*			*Condition 2*		
	EOG	*V4*	*V7*	*EOG*	*V4*	*V7*	*EOG*	*V4*	*V7*	*EOG*	*V4*	*V7*
2	62 ± 9	34 ± 7	25 ± 4	96 ± 3	97 ± 4	**99 ± 2**	68 ± 7	28 ± 7	30 ± 8	89 ± 4	96 ± 3	96 ± 3
3	86 ± 8	55 ± 9	55 ± 7	94 ± 4	**98 ± 2**	98 ± 3	84 ± 6	52 ± 7	49 ± 5	96 ± 3	97 ± 3	98 ± 2
4	96 ± 4	66 ± 7	63 ± 6	96 ± 4	97 ± 3	97 ± 3	90 ± 3	67 ± 5	61 ± 7	95 ± 4	95 ± 4	97 ± 3
5	96 ± 4	83 ± 6	78 ± 5	96 ± 2	**98 ± 2**	**99 ± 3**	**97 ± 4**	78 ± 4	73 ± 8	97 ± 4	*98 ± 3*	98 ± 2
6	**97 ± 2**	**86 ± 4**	**84 ± 7**	**98 ± 2**	**98 ± 2**	98 ± 3	**97 ± 3**	**89 ± 4**	**87 ± 6**	**99 ± 2**	97 ± 5	**99 ± 1**
B	*94*						*95*					

Table 3 Selection 1: Clustering results in percentages of *k*-means (*k* equal to 2, …, 6) without and with feature value normalisation to [0,1] for cosine and correlation distance measures. EOG denotes the results of the EOG data set, V4 the VOG data set with four features and V7 with seven features. The best value or values of every selection (column) are given in bold face and their mean is *B*

	With normalisation						*Without normalisation*					
	Cosine distance measure											
	Condition 1			*Condition 2*			*Condition 1*			*Condition 2*		
k	*EOG*	*V4*	*V7*	*EOG*	*V4*	*V7*	*EOG*	*V4*	*V7*	*EOG*	*V4*	*V7*
2	53 ± 6	24 ± 6	25 ± 7	93 ± 2	**99 ± 2**	**98 ± 2**	55 ± 6	843 ± 9	28 ± 4	91 ± 5	94 ± 3	96 ± 4
3	79 ± 4	42 ± 7	41 ± 9	87 ± 6	97 ± 4	*98 ± 3*	82 ± 6	61 ± 9	40 ± 6	88 ± 7	95 ± 4	97 ± 2
4	91 ± 3	60 ± 6	65 ± 8	93 ± 4	97 ± 2	96 ± 1	93 ± 3	72 ± 8	56 ± 7	95 ± 3	95 ± 6	**99 ± 2**
5	**96 ± 4**	73 ± 7	79 ± 7	93 ± 2	98 ± 3	**98 ± 2**	95 ± 3	83 ± 3	66 ± 9	**97 ± 4**	96 ± 5	**99 ± 2**
6	**96 ± 3**	**83 ± 6**	**84 ± 5**	**97 ± 2**	97 ± 3	**98 ± 4**	**98 ± 2**	**88 ± 4**	**76 ± 4**	**97 ± 3**	**97 ± 3**	98 ± 2
B	*93*						*93*					

Table 3 Selection 1: Clustering results in percentages of *k*-means (*k* equal to 2, …, 6) without and with feature value normalisation to [0,1] for cosine and correlation distance measures. EOG denotes the results of the EOG data set, V4 the VOG data set with four features and V7 with seven features. The best value or values of every selection (column) are given in bold face and their mean is *B* (continued)

	Correlation distance measure											
	Condition 1			*Condition 2*			*Condition 1*			*Condition 2*		
	EOG	*V4*	*V7*	*EOG*	*V4*	*V7*	*EOG*	*V4*	*V7*	*EOG*	*V4*	*V7*
2	49 ± 9	20 ± 5	18 ± 4	93 ± 6	98 ± 2	**98 ± 2**	60 ± 5	42 ± 9	25 ± 7	88 ± 5	94 ± 4	95 ± 4
3	76 ± 7	43 ± 9	43 ± 6	90 ± 3	97 ± 3	97 ± 3	87 ± 6	57 ± 5	40 ± 7	88 ± 5	96 ± 3	97 ± 3
4	92 ± 4	59 ± 7	60 ± 9	93 ± 4	96 ± 3	**98 ± 3**	92 ± 5	69 ± 8	52 ± 4	93 ± 4	97 ± 3	98 ± 2
5	93 ± 5	71 ± 7	76 ± 7	**96 ± 4**	97 ± 3	97 ± 3	95 ± 4	78 ± 7	62 ± 8	95 ± 4	98 ± 2	98 ± 4
6	**96 ± 3**	**83 ± 3**	**80 ± 7**	**96 ± 3**	**99 ± 1**	**98 ± 2**	**99 ± 2**	**89 ± 6**	**78 ± 7**	**96 ± 3**	**99 ± 2**	**99 ± 2**
B				*92*					*93*			

We also computed means *B* of the best accuracies of the columns to roughly estimate possible differences between distance measures and with or without normalisation. Whether the normalisation of the features was applied revealed no differences. For the results within single distance measures, the situations varied slightly, but generally there were no differences between their best values. In most of all cluster numbers there were none, but occasionally differences greater than 5% appeared between the use of V4 and V7 for 2–4 clusters of condition 1 in the VOG data set. Considering still the means of the best values and comparing the four distance measures with each other we noticed that there were virtually no differences between them.

Next we ran tests using *k* nearest neighbour searching, linear and quadratic discrimination analysis, and naïve Bayes rule. All tests were implemented similarly to that mentioned above for clustering. Nonetheless, we did not normalise feature values except in *k* nearest neighbour searching. Since there were *k* (>1) nearest neihgbours involved in every classification instead of 1 compared to all other classification methods, we did not use directly majority vote. The verification procedures in Section 4 were modified to indicate a correct verification in condition 1 provided that

$$\frac{x}{ka} > \frac{a-1}{a-1+bc},$$

where *a*, *b* and *c* were defined in Section 4 and *k* is the number nearest neighbours and *x* equals the number of correctly classified saccades of subject *i*. Here the left side was compared to the a priori probability of a correct verification. For condition 2 the opposite operator (≤) was employed since correct verification decisions then corresponded to matching with non-users' saccades more frequently than with those of a right user. The results are presented in Tables 4 and 5. The Euclidean distance measure was applied to these tests.

While running *k* nearest neighbour searching its maximum was 11, since no more than 12 saccades were used for a right user, in other words, for the smaller class.

According to Table 4, the tests of condition 1 were classified better than for condition 2. According to Table 5, linear discriminant analysis generated the best results for condition 1. Instead, quadratic discriminant analysis was best in condition 2.

Table 4 Selection 1: Results in percentages for *k* nearest neighbour searching (*k* equal to 1, 3, 5, 7, 9, or 11). EOG denotes the results of the EOG data set, V4 the VOG data set with four features and V7 with seven features. The best value of each column is given in bold face

	Condition 1			*Condition 2*		
k	*EOG*	*V4*	*V7*	*EOG*	*V4*	*V7*
1	73 ± 8	82 ± 6	82 ± 6	58 ± 9	**74 ± 8**	63 ± 5
3	82 ± 6	84 ± 5	89 ± 5	62 ± 7	73 ± 5	67 ± 7
5	86 ± 6	88 ± 3	87 ± 5	**66 ± 7**	71 ± 7	**68 ± 9**
7	**87 ± 6**	**89 ± 4**	**91 ± 4**	59 ± 6	65 ± 9	64 ± 8
9	85 ± 4	88 ± 2	89 ± 2	51 ± 7	58 ± 4	57 ± 3
11	82 ± 3	87 ± 1	87 ± 2	60 ± 6	51 ± 6	53 ± 8

Table 5 Selection 1: Results in percentages for linear and quadratic discriminant analysis and naïve Bayes rule. EOG denotes the results of the EOG data set, V4 the VOG data set with four features and V7 with seven features. The best value of each column is given in bold face

	Condition 1			*Condition 2*		
Method	*EOG*	*V4*	*V7*	*EOG*	*V4*	*V7*
Linear discriminant	**99 ± 1**	84 ± 5	**82 ± 4**	78 ± 4	70 ± 6	76 ± 9
Quadratic discriminant	96 ± 2	**86 ± 5**	37 ± 7	85 ± 8	**83 ± 5**	**92 ± 4**
Naïve Bayes rule	97 ± 3	78 ± 3	80 ± 4	**87 ± 5**	**83 ± 7**	80 ± 7

We still computed tests for the second selection mentioned above, which incorporated more non-users and more saccades of non-users in training sets than in the first selection. On the basis of the a priori probabilities of its two classes, the right user and non-users, condition 1 could become more difficult to verify and vice versa for condition 2.

We ran *k*-means clustering tests similar to those shown in Tables 2 and 3. Nevertheless, since the results obtained were quite similar between the four distance measures, Table 6 only includes results for the Euclidean measure. They indicated how the increase of non-users' saccades in training sets significantly decreased accuracies in condition 1. On the other hand, those of condition 2 increased virtually up to 100%. The magnitudes of the changes in condition 1 were surprising, although changes were indeed expected. For condition 2 the changes were small, because the accuracies were already close to 100% in Table 2 and the a priori probabilities in selection 2 favoured condition 2.

Table 6 Selection 2: Clustering results in percentages of *k*-means (*k* equal to 2, …, 6) without and with feature value normalisation to [0,1] for the Euclidean distance measures. EOG denotes the results of the EOG data set, V4 the VOG data set with four features and V7 with seven features. The best value or values of every column are given in bold face and their mean is *B*

	With normalisation						*Without normalisation*					
	Euclidean distance measure											
k	*Condition 1*			*Condition 2*			*Condition 1*			*Condition 2*		
	EOG	*V4*	*V7*	*EOG*	*V4*	*V7*	*EOG*	*V4*	*V7*	*EOG*	*V4*	*V7*
2	28	12	10	97	**100**	**100**	21 ± 8	6 ± 2	6 ± 3	99 ± 2	**100**	**100**
3	42	18	13	99	**100**	**100**	38 ± 4	9 ± 2	14 ± 5	**100**	**100**	**100**
4	60	26	20	98	99	**100**	50 ± 8	19 ± 5	21 ± 5	99 ± 1	**100**	**100**

Table 6 Selection 2: Clustering results in percentages of *k*-means (*k* equal to 2, …, 6) without and with feature value normalisation to [0,1] for the Euclidean distance measures. EOG denotes the results of the EOG data set, V4 the VOG data set with four features and V7 with seven features. The best value or values of every column are given in bold face and their mean is *B* (continued)

	With normalisation						*Without normalisation*					
	Euclidean distance measure											
k	*Condition 1*			*Condition 2*			*Condition 1*			*Condition 2*		
	EOG	*V4*	*V7*	*EOG*	*V4*	*V7*	*EOG*	*V4*	*V7*	*EOG*	*V4*	*V7*
5	72	35	26	99	99	98	56 ± 7	28 ± 5	22 ± 7	**100**	**100**	**100**
6	**78**	**46**	**34**	**100**	99	99	**63 ± 9**	**36 ± 8**	**34 ± 9**	**100**	**100**	**100**
B	*76*						*72*					

Finally, we tested nearest neighbour searching (Table 7) and the other three classification methods (Table 8). Compared to the results in Table 4, the method of nearest neighbour searching gave slightly better results for condition 2, as expected, but only a few percent poorer for *k* equal to 1 in condition 1. Linear and quadratic discriminant analysis and Bayes rule altered the best results of condition 2 from Table 5 to Table 8.

Table 7 Selection 2: Results in percentages for *k* nearest neighbour searching (*k* equal to 1, 3, 5, 7, 9, or 11). EOG denotes the results of the EOG data set, V4 the VOG data set with four features and V7 with seven features. The best value of every column is given in Bold face

	Condition 1			*Condition 2*		
k	*EOG*	*V4*	*V7*	*EOG*	*V4*	*V7*
1	69 ± 5	79 ± 4	80 ± 6	**70 ± 8**	**80 ± 5**	75 ± 5
3	83 ± 6	88 ± 2	87 ± 5	66 ± 12	72 ± 8	**76 ± 6**
5	86 ± 5	86 ± 6	87 ± 4	62 ± 9	69 ± 11	75 ± 5
7	86 ± 5	89 ± 3	89 ± 3	61 ± 8	67 ± 5	73 ± 6
9	**90 ± 4**	**90 ± 4**	**91 ± 6**	58 ± 8	69 ± 7	67 ± 8
11	87 ± 5	88 ± 3	89 ± 2	54 ± 5	60 ± 7	60 ± 7

Table 8 Selection 2: Results in percentages for linear and quadratic discriminant analysis and naïve Bayes rule. EOG denotes the results of the EOG data set, V4 the VOG data set with four features and V7 with seven features. The best value of each column is given in bold face

Method	*Condition 1*			*Condition 2*		
	EOG	*V4*	*V7*	*EOG*	*V4*	*V7*
Linear discriminant	89 ± 6	**87 ± 4**	**84 ± 3**	89 ± 6	87 ± 4	87 ± 3
Quadratic discriminant	**97 ± 2**	85 ± 3	25 ± 2	93 ± 4	89 ± 4	**98 ± 2**
Naïve Bayes rule	90 ± 2	65 ± 3	69 ± 3	**98 ± 3**	**97 ± 2**	92 ± 4

6 Conclusion and discussion

In the following we draw conclusions on the results obtained. On the basis of Tables 2-8 nearest neighbours produced poorer results for condition 1 compared to those of other methods. Further, selection 2 was more successful for condition 2 than selection 1 according to Tables 4 and 7. Although the results for condition 2 could be improved from selection 1 to selection 2, the results for condition 1 did not drop. Unlike with the other methods, the results of *k*-means clustering for condition 1 were greatly impaired along with this change, where clustering favoured the majority class of non-users. Instead, linear and quadratic discriminant analysis and naïve Bayes rule were fairly intolerant of it in condition 1, but could improve results in condition 2. Neither normalisation nor choice of distance measure seemed to affect the results in clustering.

Computing with or without normalisation did not lead to differences in these data sets, but since the scales of the seven features applied are very different, it is reasonable to return to this issue later in the future research after having collected larger VOG data sets. Viz., latency and duration are roughly in [0.05,0.5], amplitude in [10,70], accuracy in [–40,30], maximum velocity in [100,1100] and maximum acceleration and deceleration in [10000,100000]. The current VOG data was our preliminary data set. In the VOG data the differences between the results of either four or seven features varied and were mostly small, a few percent. Thus both could be applied.

The results introduced could not be easily compared with the results of the verification tests presented for fingerprints and face images, among others, since these test situations and methods were very different. However, looking at classification accuracy values only, our results turned out well. It was possible to verify a right subject (condition 1) up to 90% and even close to 100% with the EOG data and also to detect an imposter as such at its best for the current data. For those other eye movement or related results (Bednarik et al., 2005; Kapczyński et al., 2006; Kasprowski and Ober, 2004), they obtained various results for subject identification. For 9 subjects they obtained average false acceptance rates of 1.4-17.5% and average false rejection rates of 12.6-35.6% depending on a classification method (Kasprowski and Ober, 2004), for 47 subjects average false acceptance rates of 4.8% and average false rejection rates of 9.4% (Kapczyński et al., 2006), and for 12 subjects 90% accuracy based mostly on distance between eyes (not actually on eye movements) (Bednarik et al., 2005). Nearest neighbour searching yielded false acceptance rates of 5.4 % and false rejection rates of 56.6 %, but C4.5 trees gave poor false acceptance and good false rejection rates (Komogortsev et al., 2010). Altogether, they recorded 68 subjects, but only 41 subjects passed criteria set for the analysis. Our highest accuracies were better than those of the few other studies published so far.

Although EOG recordings are not relevant in the planned routine use of eye movements for the verification of users because of the skin electrodes needed, they were useful in the present research to predict how the results might have been better while waiting for more effective videocamera systems in the future regarding their sampling frequency (frame rate per second). As was seen, the results obtained with EOG were sometimes (for condition 1 in Tables 2, 3 and 6) slightly better than those with VOG. A probable cause is the higher sampling frequency of EOG applied, 400 Hz, compared to the low one for the VOG data, 30 Hz only. There are VOG systems with higher frequencies up to at least 500 Hz, but they are expensive. After all, we also showed here that it is possible to verify a user with a low frequency camera, which is a beneficial property when considering the use of eye movement for verification.

As one-dimensional signals eye movements can be fairly easily measured and rapidly analysed in the theoretical time complexity sense compared to image data. Eye movements can also be measured in difficult circumstances such as in dim light. The stimulation can be run within one minute, which is enough to include 30–40 saccades, perhaps only in 30–45 s.

What could be possible problems concerning user verification based on eye movements? Falsification is out of the question here since it is virtually impossible to imitate some one else's eye movements. Modern videoacameras can function well in difficult circumstances regarding illumination and temperature. An interesting issue is ageing (Lanitis, 2010) for most biometric techniques. Saccades may become slower with age, which would decrease, e.g., maximum velocity and latencies could become longer. However, the meaning of such possible phenomena is negligible in the current context of user verification, because this can always be implemented so that the verification system is adaptive, where after each acceptable login the training data buffer of the users' saccade features would be updated with a new item, leaving out the oldest one. A few dozen items would be sufficient in such a data buffer. Thus the period from which the content of the buffer is collected would be short, perhaps a few weeks. Moreover, computers, mobile phones etc. are seldom used for more than five years. A more drastic effect on eye movements might be caused by some disease affecting eye movements (Henriksson et al., 1980; Juhola et al., 1997, 2007; Pyykkö et al., 1984). These, however, are very infrequent. The adaptation property of the verification system would then be very useful.

A problem could be a possible variability in individuals' saccade feature values. If a subject's saccades vary too much at short intervals, say during days, this may cause difficulties in distinguishing his or her saccades from those of others. However, such studies have been reported showing no significant differences between different measurement times. For instance, no statistically significant differences had been obtained when average maximum velocities of 58 healthy subjects were computed within an interval of two weeks (Bollen et al., 1993). Nevertheless, we are going to study this matter in the future.

In the future we shall collect measurements from more subjects and develop our technique on the basis of the research introduced. We believe that eye movements could be used for verification when eye movement videocamera systems are used like webcameras at the moment. The encouraging results of the verification experiments presented support these objectives well. There are still several other classification methods worth testing. Logistic discriminant analysis has sometimes been effective. Like support vector machines they are designed for binary classification in particular. Neural networks such as multilayer perceptron networks, learning vector quantisation networks, self-organising maps (Kohonen networks), and radial basis function networks are possible, but neural networks frequently require a large amount of training data. Thus their use might be complicated. Decision trees may cope well with small amounts of data and imbalanced class distributions.

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