On Biometric Verification of a User by Means of Eye Movement Data Mining

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***Abstract*—In biometric verification, a signal, image or other dataset is measured from a subject to detect him or her to be or not to be an authenticated subject such as the user of a computer. So far, biometric verification has mainly been on the basis of fingerprints or face images, infrequently other images, e.g., iris. We studied the idea to apply fast eye movements called saccades to verify an authenticated user from among other subjects. We recorded eye movement signals with eye movement cameras using a suitable visual stimulation for a subject. By means of machine learning methods, we classified a subject's eye movements to verify whether one was an authenticated user. We employed multilayer perceptron networks, radial basis function networks, support vector machines and logistic discriminant analysis for classification. The best accuracy results obtained were approximately 90% and showed that it is possible to verify a subject according to saccade eye movements.**

Keywords-biometric verification; eye movements; saccades; multilayer percetron neural networks; radial basis function networks; support vector machines; logistic discriminant analysis

I. INTRODUCTION

So far, various biometric data sources have been used to verify a subject. Mostly fingerprints [1, 2] and face images [3] are applied to this task. Other images measured from subjects such as iris images [2, 4] are also studied. In addition to these two-dimensional data sources, one-dimensional signals are also used, e.g., voice signals [5]. Usually, these datasets contain an abundance of data and several variables are computed from them to ground the verification procedure on variable values of different subjects. Data mining tasks needed here may be complicated because of complex data.

Eye movements are a new potential alternative for biometric verification. Eye movements have been researched for decades in medicine. During the past 15 years eye movements have become an important research objective for human-computer interfaces. Along with these applications efficient eye movement cameras have been developed. Since there is long-term experience in the signal analysis of eye movements, for example [6-8], for biomedical and physiological applications, it was a direct development to attempt to utilize them for biometric verification of a subject simulating a computer user. Note that verification corresponds to the binary classification between two classes: an authenticated user and other subjects.

There are a few different eye movement types such as saccade, nystagmus, smooth pursuit and vestibulo-ocular reflex eye movements [7]. Probably the most frequent of all are saccades which are made while looking at surroundings or reading a text. In addition, they are very fast, in fact the fastest movements of man. They are easy to visually stimulate and their recording does not require more time than a few minutes for our tests. Those other eye movement types would require longer recordings or more complicated stimulation arrangements [7]. For these reasons, we chose saccades to be our data sources here, particularly after observing differences between saccades of individuals [7].

Up to now, a couple of attempts only have been published about this idea to use eye movements for biometric verification. In one research [8] they recorded saccade eye movement signals to compute cepstrum from these and classified signal analysis outcomes by using naïve Bayesian method, nearest neighbour searching, decision trees as well as support vector machines. In another research [9] they used a computational oculomotor model on the parameters of which verification was based using nearest neighbour searching and decision trees. Our approach differs from those since we use physiological variables computed from eye movement signals. Most of these variables have been employed for long in biomedical investigations [6,7].

II. EYE MOVEMENT DATA

We recorded saccade eye movements with a two-camera system (Visual Eyes, Micromedical Technologies, UK). Its resolution is 320×240 and sampling frequency or frames per second 30 Hz. The camera system recognized positions of each pupil from successive images of a video stream to detect eye movements. The system records horizontal and vertical signals, but we used the horizontal direction only. We wanted to keep the arrangement as simple as possible for stimulation design so that this was simple for a subject in order to avoid complex stimulations. Furthermore, using simple stimulations means that long recordings are not necessary which is important to see this biometric verification idea as sensible. On the other hand, the more data from each individual, the easier it is perhaps to separate him or her from the group of other subjects. The sampling frequency of 30 Hz was low compared to other typical ones used in eye movement camera systems such as 50 or 60 Hz, occasionally even higher like 200 Hz. Nevertheless, it was interesting to see whether this low sampling frequency allowed verification. Perhaps using a higher frequency in the future could only better results because of more accurate variable values to be computed. The system included one camera for each eye embedded in the mask attached tightly with a headband. The one of lower noise level of two eye movement signals was used for verification. Usually, both are almost identical.

We used the same stimulation series for every subject. This is, of course, the essential detail for biometric verification so that we can assume that every subject has followed the same stimulation by his or her gaze and we can classify them according to their eye movements. Each subject saw a horizontally jumping LED light dot in front of him or her. The stimulation component of the eye movement recording system included a horizontal LED bar in which one LED was switched on for a while, then switched off and another switched on immediately, and so on, by varying the LED to be next switched on. This way different gaze angles were formed. Intervals between light dot jumps were varying to make them random for a watching subject. Since intervals of 1-3 s were short and varying, the spectator could learn neither them nor varying stimulation angles. Varying, "random" intervals are important to minimize anticipations of a subject while waiting for the next stimulation movement. Anticipation would occur if latency or reaction time from the beginning of a stimulation movement to the beginning of its response, saccade, were shorter than 0.120 s seen as a minimum latency in the physiological sense [7]. It takes some time for the brain to observe a movement and control the response to move the eyes.

The present stimulation arrangement was used to simulate the beginning of a computer session where a user would first sit down to start the machine and to wait for its initialization. We can imagine that the eye movement stimulation would be run immediately after the initialization by stimulating a subject with a few dozen stimulation movements on the screen of a computer or mobile device. Thereafter, the verification procedure would be run.

We used saccades with the largest stimulation amplitudes of around 48 ° only since saccades of such large amplitudes contain greater differences between subjects than those with small amplitudes [7]. Great differences between subjects aid in verification. Nonetheless, there were smaller stimulation angles between large to give a random character between stimulations from a spectator's viewpoint. Consequently, we obtained 20 large amplitude saccades from every subject. Values of saccade variables depend on saccade amplitudes. Thus, we used merely the saccades of the largest stimulation amplitude,

For the sake of the low sampling frequency of 30 Hz, we interpolated every signal with a cubic spline method up to 1000 Hz. The purpose here was to simulate a sampling frequency of the newest, expensive high resolution eye movement cameras and, most of all, to estimate values of eye movement variables more precisely than enabled by the original signals sampled at 30 Hz.

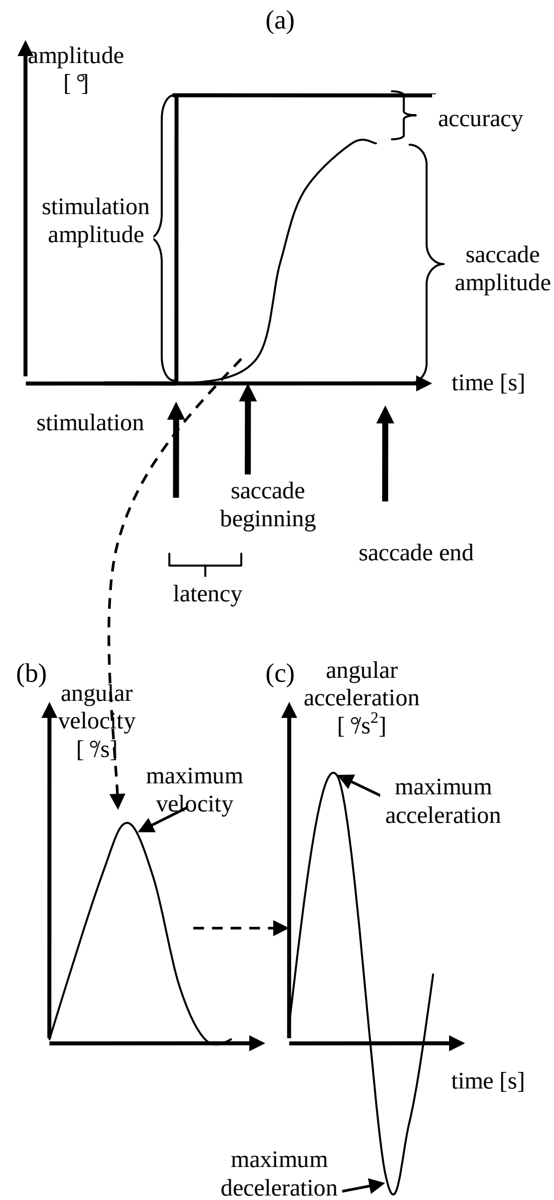

Figure 1. (a) The step (broken line) is a stimulation movement produced by a horizontally jumping light dot from the left (down in the figure) to the right (up). A saccade as a response follows it after a latency. The difference between amplitudes determines a negative accuracy, because the saccade amplitude is smaller here. A positive accuracy is also possible, but is more infrequent than negative. In our tests these values were used as absolute. Accuracy, amplitude and latency were three variables used. (b) From the saccade signal the first derivative approximation of the velocity curve is computed from which (c) the second derivation of the acceleration curve is approximated. The maximum velocity, maximum acceleration and maximum deceleration were other three useful variables to be computed.

III. SIGNAL ANALYSIS AND DATA PREPROCESSING

Fig. 1 depicts an ideal saccade and its stimulation as a schema. The first signal analysis task is to detect the exact beginning and end of every stimulation movement and those of the following response eye movement, saccade.

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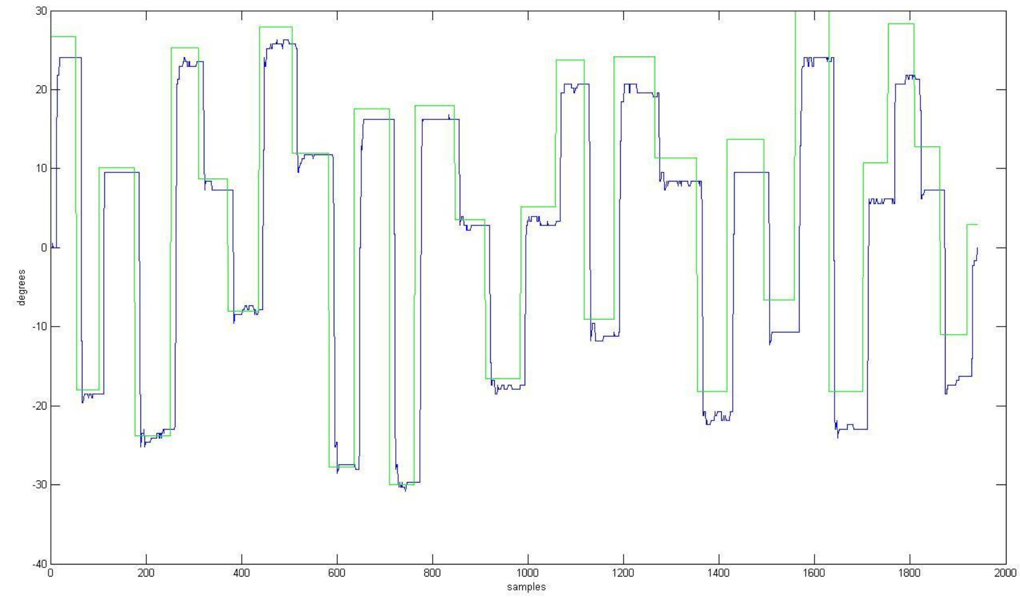

Figure 2. A smooth (green) stimulation signal of 64 s sampled at 30 Hz and its (blue) response with saccades.

The former is easy to detect since it is a clear step in a signal. The latter may rarely be somewhat corrupted by noise or artifacts such as blinks; See Fig. 2, including horizontal saccades.

If a saccade is inaccurate, its amplitude clearly differs from that of its stimulation. The brain can rapidly produce a corrective saccade with a small amplitude to correct the gaze closer to the objective. One cannot sense this correction movement, but it is "automatic". We did not include possible, quite infrequent corrective saccades, but determined the accuracy of a saccade along with the primary saccade as usual. A response to its stimulation movement had to resemble a real saccade sufficiently to be accepted for further use in signal analysis. In principle a subject might not occasionally follow the target with the gaze. This would yield no saccade at all. Anticipation as a too early eye movement including a latency value less than 0.120 s or even a saccade before a stimulation would be rejected as no actual responses to stimulations. The quality of signals given by the camera system was high with low noise. Thus, rejections of eye movements from signals were infrequent, no more than a few per cent of all saccades.

The same stimulation movements (Fig. 2) were run for every recording, so that eye movements of subjects were comparable with each other. A stimulation series included four stimulations with the largest amplitude of 48°. Five recordings were run successively from every subject giving 20 large saccades for a subject.

The five recordings of each subject formed our data for biometric verification tests. The stimulation series also contained saccades of smaller amplitudes between those four large to make the stimulation series more random-like for a subject not able to guess the direction or amplitude of a stimulation movement or an interval between two successive stimulations. Intervals were 1-3 s within a recording of 64 s.

After the interpolation of signals, the first derivative and second derivative were computed with approximation formulas such as two-point central difference differentiation [8] from each eye movement signal. A saccade beginning was found provided that absolute velocity values rapidly increased above a threshold of 50 °/s and the corresponding saccade end was found when velocity decreased back below that threshold. After detecting a saccade and ensuring that it was valid according to latency criterion, etc., all its variable values were computed and stored: amplitude, accuracy, latency and maximum velocity, acceleration and deceleration.

During recordings, a sitting, alert, relaxed subject was asked to follow the stimulation light dot by the gaze. In all, we recorded five successive recordings from healthy 132 subjects from whom 33 were females and 99 males. Mean and standard deviation of their ages were 26.2 ± 7.2 years. Neither alcohol nor medications were used during 24 h before a measurement. We wanted to test mainly young subjects in a pretty homogeneous dataset to create a strict testing basis. Age, alcohol or medications may have influence on values of saccade variables. Means and standard deviations were the following: amplitude 48.0 ± 13.4°, accuracy 3.2 ± 8.4°, latency 0.269 ± 0.057 s, maximum velocity 1038 ± 322 °/s, maximum acceleration 47591 ± 23166 °/s^2 and maximum deceleration 44845 ± 24745 °/s^2.

IV. VERIFICATION PROCEDURE

In biometric or whatever user verification, we have to prepare two opposite conditions: a subject attempting to log in is either authenticated user or impostor. Thus, we built our test procedure to take these two conditions into account.

When machine learning algorithms are used, we have to construct a training set and its corresponding test set. The content of these two sets are varied on the basis of available data. In the current case, our eye movement data were quite limited. Although there were several subjects, the bottle neck for tests was the small number 20 of saccades of the largest amplitude. Therefore, we implemented two experimental test settings called Alternatives 1 and 2. In the one of them for every subject there were either three recordings (12 saccades) in a training set and the rest of two recordings (q=8 saccades) in the corresponding test set. In the other there were four recordings (16 saccades) in a training set and one recording (q=4 saccades) in its test set. Since from every subject there were five recordings all in all, we obtained c=10 different combinations of a training set and a test set from five recordings for the former Alternative 1 and c=5 combinations for the latter Alternative 2. These were prepared for every of n=132 subjects. Our aim was to test our data as broadly as possible as conventional while applying data mining methods for classification.

Our verification task (Fig. 3) comprised two classes. Therefore, it was best that the number of saccades of an authenticated user and that of other subjects now called nonusers were not very imbalanced. We had either m=12 (Alternative 1) or m=16 (Alternative 2) saccades of an authenticated user in a training set. We then took one saccade randomly from either 2m=24 or 32 nonusers to test Condition 1 (an authenticated user) and, in addition, still one saccade to represent an impostor from q=8 or 4 other random subjects. Nonusers and impostors were naturally represented by different random subjects from among n-1=131 subjects (an authenticated user excluded). At first, we implemented tests with this approach since we may assume that randomly selected subjects represent a more extensive area in the variable space than one authenticated. Nonetheless, we noticed that better results could be obtained by once copying the saccades of an authenticated user to balance the class size of an authenticated user's class and that of nonusers to be equal 2m. Copying once m saccades of the former increased the density of these saccades in a dataset.

In the verification procedure, the following symbols are also employed. All tests were repeated r=10 times since there were random choices of saccades of nonusers and impostors and also random initializations, among others, in multilayer perceptron networks. To test the remaining q saccades were taken to a test set where q was equal to 8 (Alternative 1) or 4 (Alternative 2). Symbols TP and FN equal the numbers of true positive and false negative decisions in classifications and FP and TN those of false positive and true negative decisions. On the basis of the two former, a decision for a subject is made whether a test subject is an authenticated user (Condition 1). Correspondingly, the two latter are used for a decision whether a test subject is an impostor (Condition 2).

$C1_1$=$C2_1$=$C1_2$=$C2_2$=0; % counters for correct classifications of authenticated users and those of impostors

For h=1:r % iterations of the main loop
 For i=1:n % one by one as an authenticated user
  TP_2=TN_2=FP_2=FN_2=0 (Alternative 2);
  For j=1:c % c combinations of recordings
   Take m saccades from 3 (Alternative 1) or 4 (Alternative 2) recordings of an authenticated user to a training set;
   Copy these m saccades in the training set;
   Take randomly 2m nonusers and one saccade from each and add these saccades to a training set;
   Train a model with 4m saccades of two classes: an authenticated user and nonusers;
   TP_1=TN_1=FP_1=FN_1=0 (Alternative 1);
   For j=1:q % tests of Condition 1
    Classify a test saccade of an authenticated user into either correct class
    TP=TP+1
    or incorrect class
    FN=FN+1;
   End
   For k=1:q % tests of Condition 2
    Classify a test saccade of an impostor into either correct class
    TN=TN+1
    or incorrect class
    FP=FP+1;
   End
   % Follow majority vote for decision
   If $TP_1 \geq FN_1$ **then** $C1_1$=$C1_1$+1 (Alternative 1);
   If $TN_1 > FP_1$ **then** $C2_1$=$C2_1$+1 (Alternative 1);
  End
  % Follow majority vote for decision
  If $TP_2 \geq FN_2$ **then** $C1_2$=$C1_2$+1 (Alternative 2);
  If $TN_2 > FP_2$ **then** $C2_2$=$C2_2$+1 (Alternative 2);
 End
End

(Alternative 1)
Accuracy of authenticated users=100 % · $C1_1/(r \cdot n \cdot c)$
Accuracy of impostors=100 % · $C2_1/(r \cdot n \cdot c)$
(Alternative 2)
Accuracy of authenticated users=100 % · $C1_2/(r \cdot n)$
Accuracy of impostors=100 % · $C2_2/(r \cdot n)$

Figure 3. Verification procedure for authenticated users (Condition 1) and impostors (Condition 2). Two different test settings are called Alternatives 1 and 2.

V. Classification Results and Discussion

The main data mining task was to classify test saccades into two classes: an authenticated user or nonusers. There were n=132 subjects and r=10 main iterations in the verification procedure yielding 13200 decisions in Alternative 1 and 1320 decisions in Alternative 2.

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TABLE I. CLASSIFICATION ACCURACIES OF MLP NETWORKS WITHOUT NORMALIZATION: MEANS AND STANDARD DEVIATIONS IN PERCENTS (*ON* EQUALS THE NUMBER OF OUTPUT NODES AND *C* CONDITIONS 1 AND 2)

Accuracies for two test alternatives, output node numbers *ON* and conditions *C*						
Alter-native	***ON***	***C***	***Number of hidden nodes***			
			4	6	8	10
1	1	1	71.8±0.8	70.8±0.9	**71.0±1.6**	70.4±0.8
1	1	2	64.9±0.7	65.2±1.8	**66.5±1.4**	66.4±0.9
1	2	1	72.1±1.2	71.8±1.3	**72.2±0.8**	71.7±1.1
1	2	2	66.8±1.5	66.8±1.5	**66.8±1.7**	67.0±1.5
2	1	1	78.5±3.3	79.6±3.4	78.9±2.5	**78.5±2.5**
2	1	2	74.2±3.1	78.0±3.4	79.8±3.6	**80.8±2.6**
2	2	1	81.9±2.8	**82.6±3.2**	82.2±3.5	79.8±2.8
2	2	2	77.8±1.9	**78.6±3.0**	78.6±2.7	79.2±3.0

TABLE II. CLASSIFICATION ACCURACIES OF MLP NETWORKS WITH NORMALIZATION AND ALTERNATIVE 2: MEANS AND STANDARD DEVIATIONS IN PERCENTS

Accuracies for output nodes and conditions					
Output nodes	***Condition***	***Number of hidden nodes***			
		4	6	8	10
1	1	81.1±2.7	78.4±3.9	**78.9±2.6**	78.4±2.5
1	2	75.8±2.4	79.5±3.2	**81.1±3.6**	80.5±3.2
2	1	80.5±1.8	80.1±4.2	80.0±4.5	**79.6±2.6**
2	2	77.3±2.4	81.7±3.6	80.2±4.3	**82.7±2.5**

We applied multilayer perceptron (MLP) networks [9] with 6 input nodes (6 variables), 4, 6, 8 or 10 hidden nodes and 1 or 2 output nodes for two classes. A validation error was used for MLP networks. It automatically stopped training after 9 or 10 epochs to avoid overtraining. Since we used the backpropagation algorithm in Matlab (MathWorks Inc., USA) also used for all tests of our research, we experimented with its training procedure variations including the adaptive learning rate, Powell-Beale restarts, batch gradient descent with momentum and Levenberg-Marquardt algorithm [10]. For actual tests we used the last method that yielded slightly better results than those of the other.

At first, we investigated possible differences between test results of Alternatives 1 and 2. Since the number of 5 recordings (20 saccades) of each subject was small subject to build training and test sets in data mining, it was important to test more than one alternative. However, the scarcity of the data did not allow more alternatives than the aforementioned two. We also varied the number of output nodes from 1 to 2. On the basis of the best results written in Bold in Tables I and II 2 output nodes produced accuracies 1-4% superior to those of 1 node.

TABLE III. CLASSIFICATION ACCURACIES OF LOGISTIC DISCRIMINANT ANALYSIS AND SVM WITH NORMALIZATION: MEANS AND STANDARD DEVIATIONS IN PERCENTS.

Accuracies for two test alternatives *A* and conditions *C*						
A	***C***	LogDA	***SVM kernels***			
			Linear	2^{nd} deg.	3^{rd} deg.	Gaussian
1	1	78.5±105	80.0±0.5	75.6±1.0	69.6±1.2	**84.9±0.7**
1	2	65.7±1.7	62.2±1.3	63.6±1.7	61.8±1.7	**73.0±1.3**
2	1	86.6±1.7	88.0±2.9	82.7±2.1	74.1±2.5	**92.1±1.9**
2	2	77.4±3.4	73.9±4.8	77.1±2.9	73.3±4.5	**84.8±1.9**

The scales of the variables markedly differed from each other. We tested MLP networks without and with normalization into interval [0,100]. The accuracies obtained without or with normalization had virtually no differences on an average. The results of the former are showed in Table I. Those of the latter are in Table II with Alternative 2 only, since Alternative 2 with the larger training set than with Alternative 1 indicated to be 7-13% better in Table I. The similar observation was gained for all later results. Note that while evaluating results we always have to look at both conditions at the same time, because they both are equally critical objectives. Note also that 50% is seen as a baseline result for Conditions 1 and 2. Because there are two classes of equal size, a random guess between them would be correct with probability 0.5. The number of the hidden nodes from 6, 8 or 10 yielded the best results for the pairs of Conditions 1 and 2.

We ran support vector machines (SVM) with the linear, quadratic, third degree polynomial and radial basis function (Gaussian) kernels. Table III shows results for SVM kernels and logistic discriminant analysis (LogDA). We ran tests for all four SVM kernels and logistic discriminant analysis by using both Alternatives 1 and 2 with and without normalization. Alternative 2 again generated higher results than Alternative 1. The use of normalization according to Table III did not affect average results seemingly at all compared with those not presented without normalization, mostly less than ±1%. SVM with the radial basis function (Gaussian) kernel was the best choice here, but differences were small compared with a few other kernels.

TABLE IV. CLASSIFICATION ACCURACIES OF RBF NETWORKS WITH NORMALIZATION: MEANS AND STANDARD DEVIATIONS IN PERCENTS

Accuracies for two test conditions				
Condition	***Spread and goal***			
	15 0.05	15 0.08	20 0.08	20 0.1
1	75.4±4.1	77.8±0.1	83.4±2.6	**88.5±1.8**
2	92.6±1.6	94.7±1.6	88.9±3.9	**88.9±1.9**

Ultimately, we exploited RBF networks by running system parameters of spread 10, 15, 20, 25, 30, 35, 40, 45 and 50, and goal 0.005, 0.02, 0.03, 0.05, 0.08 and 0.1. The best combinations of these were spread equal to 15 or 20 and goal equal to 0.05, 0.08 or 1.0. Final results of RBF networks are presented in Table IV. For the RBF networks, our data required normalization, because our tests (not presented here) without it favoured Condition 2 and almost entirely failed with Condition 1. Thus, the results in Table V were computed with normalization and using Alternative 2.

Since our final objective to develop a biometric verification procedure on the basis of eye movements included a criterion that computing time should be fast, it is important to look at running times of the preceding tests. There were $132\times10\times5$=6600 models trained for every test type or structure (cell) in the case of Alternative 2. For Alternative 1 there were $132\times10\times10$=13200 models trained, correspondingly. The training and test time of an MLP network was around 0.5 s on an average. For RBFs that time of one network was around 4 s and for SVMs and LogDA less than 0.05 s. Let us remember that these execution times also included training not always necessary to do while applying a data mining method in actual applications, except when the system is used for the first time and then adaptively, say, after a successful login. In any case, even the use of the slowest method here was fast enough. Of course, additional computation is needed before the data mining phase to perform signal analysis. Still, this is also very fast, because its time complexity is linear and the length of eye movement signals is short, no more than a few thousand samples, say 1-3 minutes. Consequently, the running time would be minimal compared to such a recording time. At the beginning, in the course of a recording the eye movement camera system also makes image processing, but this is also close to real time. The camera system used consisted of only an initial calibration when taken into use. Thus, calibration required no additional processing time here.

VI. CONCLUSION

The MLP networks produced their best results with Alternative 2, 2 output nodes, 6 hidden nodes in Table I and 10 hidden nodes in Table II. The use of normalization did not improve the results obtained which were around 8% poorer than the best of SVMs and RBFs in Tables III-V. The Gaussian kernel was the best choice with SVMs. RBFs were very sensitive to normalization needed apart from the other being very insensitive to normalization.

The best results obtained were fairly good as 89% of the best results in Tables IV and V. We may assess that the best realistic accuracies based on various biometric verification references are around 95%. Thus, the results of this quite novel way to perform a biometric verification task are promising although more research has to be made to improve verification accuracies. A clear chance here is to collect a larger set of recordings from each individual. There were only five recordings with four large saccades per a subject. Forming a larger training set from each subject than now it is quite probable that we are able to improve classification results based on data mining methods. To compare with other scarce results presented thus far, our results were equal or better than various values 50-90% given in [11, 12].

The eye movement camera system used included a low sampling frequency of 30 Hz (frames per second). Still, verification was fairly successive. The low sampling frequency was, however, interesting since it was similar to that often used in cheap web cameras. We may except that in the future eye movement cameras are installed in computers or mobile devices to follow a user's gaze for various human-computer interface tasks [13]. If their sampling frequencies will be higher, e.g., 200 Hz, biometric verification with eye movements may well be realistic.

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