New Pen Device for Biometrical 3D Pressure Analysis of Handwritten Characters, Words and Signatures

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ABSTRACT
The demand for biometric applications in security, human computer interaction and related areas is rapidly increasing. This paper presents an unique biometrical smart pen BiSP for personal identification and handwriting recognition that has been developed in our laboratory. The system is superior to many other biometric techniques which have considerable disadvantages in practice. Several ballpoint like prototypes based on integrated sensors have been designed and constructed. In this report we focus on BiSP systems based on pressure sensors and on microphones. Pressure sensors record the physical pressure exerted on the ballpoint pen in three dimensions during handwriting. The BiSP system based on microphones acquires the sound produced during handwriting on normal paper. Features of these devices as well as the evaluation of the recorded signals are discussed. Preliminary results of data processing show possible application areas of our new device – signature verification, writer identification and handwritten text recognition.

Categories and Subject Descriptors
B.4.2 **[Input/Output and Data Communications**]: Input/Output Devices; I.5.0 **[Pattern Recognition]:** General; G.3 **[Probability and Statistics] –** *Time series analysis*; K.4.4 **[Computers and Society**]: Electronic Commerce.

General Terms
Measurement, Algorithms, Performance, Design, Security, Human Factors, Verification.

Keywords
Biometric Identification, Multimodal Biometrics, Signature Verification, Pen-pressure Analysis, Microphone Pen, Acoustic Handwriting Recognition.

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1. BASIC CONCEPTS OF BiSP
Modern electronic communication requires handwritten and spoken text recognition, biometric personal identification and digital signature verification in many areas such as e-commerce, home banking or control of access to machines, services and security systems. Numerous unimodal biometric systems are commercially available, like fingerprint, iris and face recognition, speaker or signature verification. In practice most of these have serious disadvantages because they are intrusive, uncomfortable, costly, have low performance with respect to error rates, may be suited only for limited populations or show poor mobility or protection against imitation.

In fact, biometric identification and verification is inherently prone to errors due to considerable variability of biometric features and insufficient reproducibility of measurements. It is thus generally agreed that reliable biometric authentication requires the combined analysis of multiple behavioral traits or physiological characteristics. The ability to measure miscellaneous biometric patterns at the same time is the principal purpose and the main potential of our "biometric smart pen", BiSP [1]. In this project we are developing a unique multifunctional pen system which is superior in many respects to current pen based human computer input devices. The BiSP device is a smart ballpoint pen for data acquisition and processing by means of speech, handwriting on normal paper pads and fingerprint. It is equipped with a diversity of sensors for monitoring

- dynamics of pressure transferred in three dimensions from the refill to the pressure sensors
- time dependent horizontal x,y-position and velocity of the pen during writing
- acoustic signals generated both by handwriting on paper and speech
- fingerprint data.

In combination with common and newly developed software the BiSP pen becomes an extensive technology which can be applied

- in biometrics for highly secure human identification and verification based on physiological and behavioral characteristics generated from handwriting, speech and fingerprint
- as an essential part of a desktop covering electronic recognition of handwriting and voiced speech, for example to trans-

fer handwritten notes or draws from a normal paper pad to the computer
- in life sciences for computer added diagnostics, therapy and training tasks in medicine, physiology and education using biometric data corresponding to behavioral traits of human individuals.

The advantages of the BiSP system under progress are apparent. The BiSP pen is

- a multimodal biometrics system that includes three different biometric technologies which are considerably more accurate in combination than current single methods: handwriting, speaker and fingerprint identification and verification.
- a system which may be extended by optical sensors for biometric data acquisition, optical character recognition or cursor movements.

Several prototypes based on a variety of mechanical, optical and magnetic sensor techniques have been designed and constructed by our group holding the patent of the BiSP pen. In this paper we focus on the BiSP prototype based on pressure sensors (MechPen) and on microphones (MicPen). Results from preliminary field tests are presented below.

The schematic draw of the general multifunctional BiSP device based on mechanical sensors is shown in Figure 1.

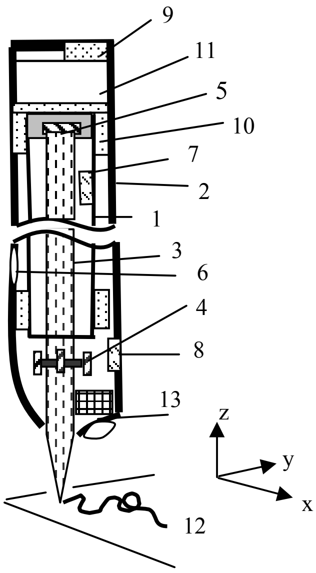

Figure 1. Block scheme of the BiSP device for data acquisition. (1) inner case (2) outer case (3) refill (4) x,y-pressure sensors (5) z-pressure and vibration sensor (6) fingerprint chip (7, 8) inner, outer microphone (9) loudspeaker (10) acoustic isolation placed between the cases (11) electronics and data storage (12) ink trail on normal paper (13) optical sensors .

2. BiSP PRESSURE PEN (MechPen)

The pressure or force resulting from handwriting on paper is transferred and monitored in horizontal x,y direction by strain gauges (4) placed orthogonal to each other in the top part of the refill (3) and in z-direction by a piezoelectric sensor (5) located at the end of the refill. The latter also monitors the vibration of the refill determined by the velocity of handwriting on a paper pad. We used metal strain gauges integrated in a half-bridge circuit. Their output signals are conditioned by a low pass filter and a single supply instrumentation amplifier providing signals in a dynamic range of 4V. The sensor (5) at the end of the refill is a miniature piezoelectric force or pressure sensor in the passive mode, sampling the change of pressure and vibration in z direction. Amplification of the signals was performed with a charge amplifier with high input impedance. The sampled signals of the three pressure sensors are digitized with a 10 bit A/D converter at a sampling frequency of 500 Hz. A picture of the first fabricated MechPen (Figure 2) shows the strain gauges in front of the refill and the electronics for signal processing and wireless transmission of data. An example of a 3D pressure signal generated by writing the character "Hello" is shown in Figure 3.

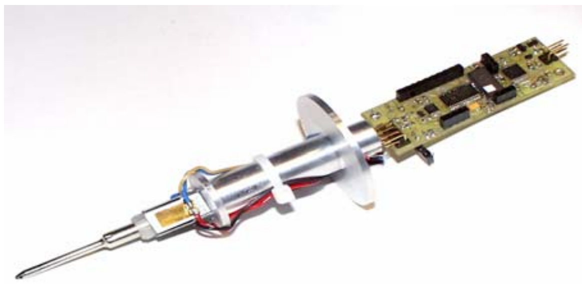

Figure 2. MechPen prototype fabricated for experimental work in our laboratory

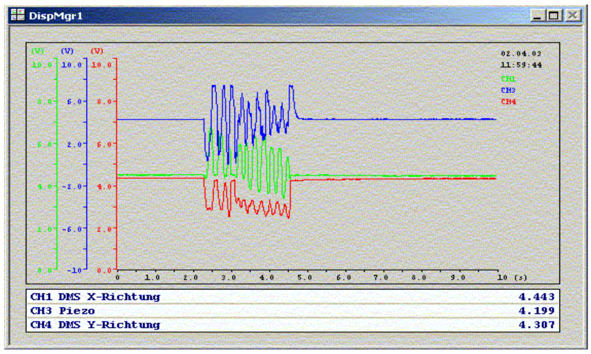

Figure 3. Pressure signals Px(t), Py(t) and Pz(t) acquired during writing the word "Hello".

3. BISP ACOUSTIC PEN (MicPen)

Audio signals generated by movement of the pen during handwriting on a pad are picked up by a microphone mounted inside the pen. The block scheme of the MicPen system with implemented standard components is given in Figure 4.

Figure 4. Block scheme of BiSP system based on a microphone.

In the MicPen configuration (see Figure 1) the microphone (7) is placed inside the inner case (1), such that the recorded signal corresponding to the sound produced during writing is transmitted through the refill (3) to the interior microphone. Undesirable signals like background noise or voiced speech are not detected by this microphone. This is achieved by using sound isolation (10) located between the outer and the inner case. As a refill (3), a standard ballpoint refill of metal, which transmits elastic waves well, was chosen. The tube of the inner case (1) works like an acoustic resonator. In addition the MicPen can record voiced speech signals or a sound originating from the pad when a microphone (8) without acoustic shielding is used. The miniature back electret microphones implemented has a spectral range of 20 Hz-16kHz. Its signals conditioned by elliptic filters and a common inverting OPAM are digitized using a 10 bit A/D converter at a sampling rate of 8 - 44,1 kHz. For signal and data processing we have applied software programmed in C++, LabView and MATLAB. As a user writes on a paper surface, the movement of the pen tip over the paper fibres generates vibrations with excitation frequencies controlled by the roughness, hardness and the velocity. The vibrations are transmitted across the refill to the microphone in the form of elastic waves. The waves are filtered by the internal mechanical components of the pen acting as oscillators or resonators. Examples of signals provided by the microphone (7) during writing on a normal paper pad are presented in Figure 5. The time signals were captured during handwriting three times the letters "a" and "b".

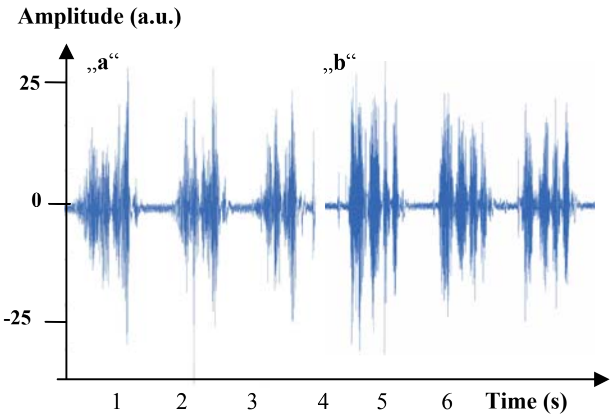

Figure 5. Three microphone time signals of letters "a" and "b", handwritten.

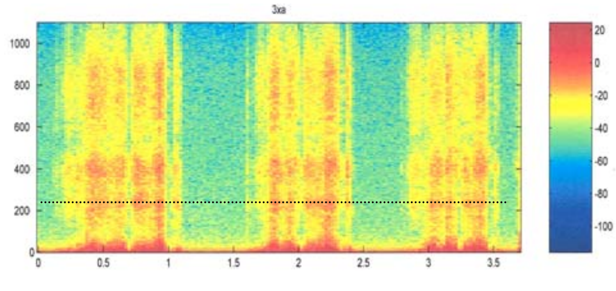

Figure 6. Three spectrograms of letter "a", handwritten

The two letters clearly differ in shape and dynamics of the amplitudes, and indicate high reproducibility of the features.
As shown in Figure 6 the corresponding spectrograms of letter "a" generated by FFT are quasi-periodic spectra in the typical range of 40-1000 Hz. The frequencies at peaked amplitudes represent fundamental frequencies or multiples of them. They are determined by the hardware configuration of the MicPen. The change of spectral amplitudes with time corresponds to the dynamics of handwriting. Its dynamic range can be considerable as illustrated in Figure 7 for amplitudes selected at the frequency of 213 Hz.

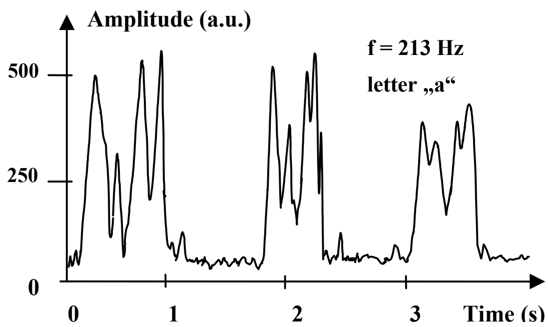

Figure 7. Time dependence of amplitude at frequency f = 213 Hz.

For a given MicPen configuration and a paper pad this time behavior is determined primarily by the speed of writing. This effect is experimentally shown in Figure 8. by drawing a 400 mm long track on a paper based pad with a uniform surface. The increase of the microphone signal with time can be explained by impact frequencies and forces increasing with the speed of movement.

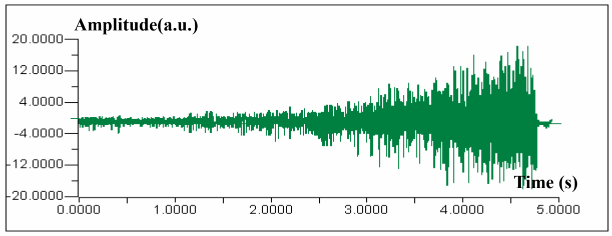

Figure 8. Time signal of the MicPen accelerated on a paper pad.

In summery the microphone signals in the time and frequency domain provide valuable dynamic features for biometrics. Experiments have been started in order to investigate parameters which mainly define the recorded signal of the MicPen and to verify the possible use of the MicPen in various applications. The applications preferred by us are signature verification, writer identification and handwritten text recognition. First results described in [2] are quite promising.

Many parallels exist between the acoustics of handwriting and voiced speech with respect to (a) sound production and sound analysis (b) application-oriented software for the recognition of spoken and handwritten text and (c) identification of hand writers and speakers. This inspires us to utilize techniques and algorithms of common speech processing in the BiSP system equipped with embedded microphones [3]. This BiSP system allowing the identification of hand writers and speakers by the same device is unique and protected by a patent.

4. SOFTWARE

A prerequisite for the broad functionality of our BiSP-system is the development of a software-engine for various modes of application, with access to arbitrarily large databases, high throughput rates, real-time authentication, and the option to meet stringent demands on reliability and security.

In accordance with the existing pen configuration, our primary focus was the development of algorithms evaluating typological traits manifest in Px, Py and Pz pressure signals of handwritten characters, text or signatures. In order to cope with large data bases of templates, the software system is composed of successive hierarchical levels, realizing a forward and backward sequence between progressively coarse or, vice versa increasingly detailed classification and matching operations.

At the first stage of the program, global statistical properties of the signals are analyzed after adequate preprocessing of the original data. Global properties are intrinsically robust and represent highly compressed and reproducible information [4]. Regional and morphological features of segmented pressure signals contain increasingly detailed information but are difficult to access, may be less reproducible and are thus reserved for later stages in our hierarchical authentication process [5].

Our preliminary algorithm extracted about n = 110 global features from the pressure signals of each template (e.g. length, mean value, standard deviation, skewness, number of peaks, number of radial loops, sweep of polar angle, line integrals, static moments of MAV-signals, distribution of frequency spectrum, nonlinear optimization parameters, etc.).

Based on representative data from two field-tests, the statistical properties of all features were carefully examined using (1) the complete population of samples, and (2) templates collected from the same person, respectively. Features with low individual reproducibility, little overall variance, insufficient specificity and pronounced redundancy were discarded. The dimensionality of feature space was thus reduced to the order n = 50. From the distribution of each remaining feature the 1/3 and 2/3 quantils were computed, splitting the observed total range of real feature values into three intervals. In this way, on average one third of the realizations of a stochastic feature variable will be characterized as “small”, as “medium” and as “large”, respectively. Obviously, real numbers are thereby mapped to “qubits”, i.e. to the quantized states 10 (= small), 01 (= large) and a superposition of both 11 (= medium). Besides, a fourth state could be reserved for outliers 00 (= faulty). The scheme of converting a stochastic real variable to a 2 bit representation is equivalent to an extremely crisp fuzzification with respect to three (four) linguistic variables with step-like membership functions.

In summary, handwritten characters, text or signatures are compressed to n-dimensional feature vectors of bit-pairs. It should be noted that a 3-state qubit representation comprised of n = 50 stochastically independent random variables maps each written sample to one out of 10^{24} elementary hyper cubes.

4.1 Metrics and Classes

In order to reduce the computation time for online identification, the reference database of feature vectors is subjected to a classification procedure using straightforward metrics defining the similarity score. The quantized templates are compared against each other in a many-to-many matching sequence using XOR-operations for the evaluation of their Hamming distance. A specific heuristic limits the number of comparisons to the order of $N \cdot \log N$, depending on the adjustable size of a decision threshold. Subthreshold neighboring points will be assigned to the same class (i.e. grouped). Classes are allowed to overlap in space, i.e. individual templates may be located within the boundaries of more than one class. Finally, each class is represented by a prototype which is simply the qubit-representation of the algebraic mean of all (real) feature vectors within that group.

4.2 Identification

The principal steps to identify a captured sample are (a) preprocessing of original time signal (b) extraction of feature values (c) mapping to qubit representation (d) comparison against prototype vectors of classes (e) comparison against prototype vectors of individuals within selected classes (f) application of more refined techniques for remaining selection of matching templates.

Classes (as represented by their prototype vectors) which do not match the submitted sample are discarded (step d). The test vector is then compared against individual prototypes within the remaining classes. “Individual prototypes” are qubit vectors obtained from the algebraic mean of all (real) feature vectors contributed by the same person to the same class. This step leads either to a distinct score, or to a number of equivalent proposals (step e). If multiple scores are presented, the matches can be analyzed in greater detail, now comparing the test sample against the individual binary feature vectors building the selected prototypes. Alternatively, higher levels of security may require backtracking along the hierarchy, i.e. employing more refined techniques for the final association of the claimant with the remaining matches, using the original time signals (step f). Among such techniques are DTW, HMM, neural nets, AR/ARMA, covariance analysis, etc. (for an outline cf. [6]). The present work deals exclusively with the approach subsumed under steps (a) to (e). Appropriate techniques for the final identification (f), particularly the analysis of morphological characteristics, are presently being studied in cooperation with the universities of Frankfurt, Heidelberg, Passau and Pilsen.

5. RESULTS

5.1 Field Trial A

Two field trials, A and B have been performed in our lab, with distinctly different focus as to the validation of hardware and software components of the BiSP system, and the general biometric characteristics of dynamic pressure patterns.

Fifteen individuals were enrolled in the preliminary field test A, which focussed on the dynamic attributes of written characters, words and signatures under optimal conditions. Conditions are termed “optimal” because the collection of samples from a candidate was accomplished during a single session, keeping the variability low. The set of items consisted of eight primitives {A, B, O, 4, 5, 8, +, Δ}, five German words of similar length {auch, oder, bitte, weit}, a common sequence of words {Guten Morgen} and the individual signature of the participant. Each item was repeatedly written ten times in succession, such that repositioning or changing the grip on the pen did not occur. Therefore, the gathered samples were neither affected critically by the yet imperfect ergonomic design of the prototype pen, nor a displacement and rotation of the instrument between consecutive samplings. The main issues of field trial A were as follows:

- validation of hardware and software components
- comparison of samples submitted by the same individual (reproducibility test)
- comparison of feature vectors extracted from equal items written by different persons
- comparison of feature vectors extracted from different items written by the same person.

An example for great similarities between repeated pressure signals (letter “8”, same person) or otherwise, pronounced differences (letter “8”, different persons) is depicted in Figure 9. A measure for the reproducibility of written items is the mean and standard deviation of the Hamming distance, obtained from comparison of N items gathered from the same person. Expressing the score in percent (e.g. 100% = identity), 80% of digits in the quantized feature vectors match on average. Similar results are obtained for written characters, words and signatures (cf. Table 1). Interestingly, the combination “Guten Morgen” has maximum reproducibility, suggesting that certain meaningful sequences of written words may be more suitable for authentication than signatures submitted in a more or less reflex like action.

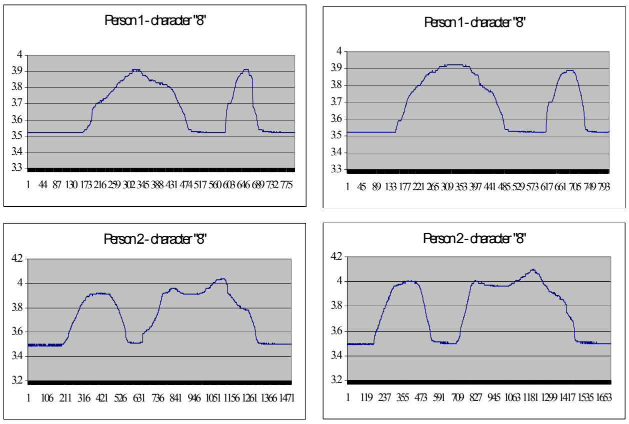

Figure 9. Pressure signal PZ(t) of written character “8“. Two persons, two trials each.

In order to discriminate between various individuals, biometric authentication requires high scores for repetitive trials from the same person and, in contrast, low scores for trials from different persons. The latter property was evaluated by cross-checking the distance of feature vectors from equal items written by person X vs. those written by person Y; X ≠ Y, (cf. Table 2). Note that in the statistical limit of infinitely large databases the mean X:Y score is 50%.

Tables 1 and 2 demonstrate that equal items written by the same person are 25% “closer” to each other than the same items written by different persons. We conclude that our software tool is adequate to discriminate between human individuals among the reference population, either by means of matching handwritten signatures or likewise words or just a sequence of isolated characters.

Table 1. Reproducibility test: Comparison of equal characters, words and signatures written ten times repetitively by same individual. Mean score and stdv calculated from 45 comparisons per item and per person. Table shows algebraic mean of the mean scores and stdv calculated from 15 enrolled individuals.

Character	A	B	O	4	5	8	+	Δ
Mean score, %	79.4	79.0	79.4	80.3	79.8	80.9	82.7	76.9
Stdv, %	6.4	6.9	6.0	5.9	6.4	5.8	6.4	7.0

Character	auch	oder	bitte	weit	Guten Morgen	Signature
Mean score, %	78.9	78.7	80.9	79.5	83.1	81.3
Stdv, %	7.0	6.4	5.8	5.7	5.4	5.2

Table 2. Comparison of equal items written by different persons X and Y. Average scores and stdv determined from 10x10 comparisons for each item and each X,Y-combination of users. Table shows algebraic mean of average scores and stdv, obtained from 15 persons (105 X,Y-pairs).

Item	A	B	O	4	5	8	+	Δ
Mean score, %	56.2	58.4	58.8	55.2	54.9	55.2	68.2	57.6
Stdv, %	6.7	6.8	6.1	6.7	6.7	6.4	6.3	6.9

Item	auch	oder	bitte	weit	Guten Morgen	Signature
Mean score, %	54.3	55.5	56.3	54.1	52.9	53.2
Stdv, %	7.2	6.8	6.4	6.7	5.9	6.3

Whether the set of biometric features is sufficiently distinct to permit secure user authentication was tested in a “leave-3-out analysis”. For each person, three signatures and three “Guten Morgen” were arbitrarily excluded from the reference database, serving as test samples for identification.

Defining “correct identification” as proper association of the claimant with his enrolled counterpart, and “correct verification” if the claimant is among the selected top three matches, we get the results shown in Table 3.

Table 3. Scores obtained from comparing signatures or “Guten Morgen”. For definition of identification and verification score see text.

Field trial A	Identification score	Verification score
Signature	89 %	98 %
Guten Morgen	98 %	100 %

As already predicted from inspecting Table 1, we have a better score rate with “Guten Morgen” than with individual signatures. Note that screening operations (elimination of outliers, etc.) have neither been conducted with the test data nor with the reference samples.

Similar results from the set of written characters lead us to a promising application, namely the evaluation of pressure signals from handwritten PIN codes. On a first run, the pressure signal of the complete code is processed (after cutting out breaks between consecutive characters) in order to verify or identify the claimant. This adds security to the common (and mostly disliked) use of the PIN by means of biometric personal authentication. In a subsequent step, isolated characters from the sequence are verified using the same algorithms, now applied to the personal reference data. These are stored characters from the identified individual. This latter process may be termed “biometric character verification”. The corresponding extension of our software system is feasible only if cross-checking of different symbols written by the same person exhibits sufficiently low score values. Results for a few combinations from our character set {A, B, O, 4, 5, 8, +, Δ} are plotted in Table 4.

Table 4. Comparison of different characters written by same person. Average scores and stdv determined from 45 comparisons per character pair and per user. Table shows algebraic mean of average scores and stdv, obtained from 15 users.

Character 1	A	A	B	B	Δ	Δ	4	5
Character 2	B	8	O	8	5	O	5	8
Mean score, %	69.0	67.8	63.2	66.3	67.2	71.7	72.3	72.1
Stdv, %	6.2	5.5	5.9	5.8	5.6	6.1	5.6	5.7

Another ultimate prerequisite for “user authentication based on handwritten characters” is, of course, a distinct separation of feature vectors extracted from different characters written by different persons. We have compared any possible combination of items i1, i2; i1≠i2 written by users X≠Y among our total reference population, resulting in an average score of 54.8 % and standard deviation of 9%. Comparison of this very low score value with the scores between 65% and 70% shown in Table 4 (case i1≠i2; X=Y) leads to the following conclusion: Due to individual behavioral characteristics in handwriting, all points in feature space associated with the same human individual are contracted to some extent. This finding supports our approach to discriminate between users through the comparison of a multitude of different items (e.g. the PIN), because these build clusters in feature space if originating in the same person.

The potential of our software to cope with the idea of a biometric PIN-verification system will be evaluated in a future field trial. At the present stage of analysis, we have tested numerous randomly selected characters against a database with 1200 entries, giving very convincing results as to their potential for user identification and character verification.

5.2 Field Trial B

The main objective of the second field trial B, was a critical validation of BiSP-hardware and software with respect to authentication measures under more realistic, i.e. non-identical conditions. Individual handwritten signatures of a representative set of enrolled persons (N = 40) were collected at different times (5 days, morning and afternoon session, respectively). A series of 10 successive signatures was written by each user during each session. Although in subsequent correlation tests, many of the collected samples proved to be outliers, no screening of the data has been performed. However, samples from the first day were completely discarded because it took considerable time for the participants to accommodate to the somewhat unhandy pen device.

In order to simulate maximum variability in a person´s signatures, one reference sample was selected from each session (i.e. altogether 8 reference samples per user, collected at days 2 to 5, morning and afternoon session, respectively). Our database thus contained 40x8 = 320 entries. The remaining data served as reservoir for the subsequent identification process. Similar to the procedure in (A), we selected three signatures per person from the test set and compared them against the prototypes of the database. In our terms “correct identification” is again synonymous to the result “test sample and best matching prototype represent the same person´s identity”. We speak of “correct verification”, if the claimant is identical to at least one out of the three topmost matching candidates (rank 3 score) and the score is above 75 %. Corresponding results are shown in Table 5.

At first glance the results depicted in Table 5 are not quite satisfactory. However, most participants required considerable time (or a large number of trials) to accommodate to the handling of the pen. This is evident from the significant increase in scores from the second to the fourth day. Taking into account that entries in the reference database are also composed of samples from both accustomed and non-accustomed users, a further improvement of results could be expected if the population of reference data was collected solely from experienced persons.

Table 5. Authentication from test signatures written at three consecutive days during the field trial. For definition of identification and verification score see text.

Field trial B	Identification score	Verification score
2nd day	60 %	77 %
3rd day	77 %	88 %
4th day	80 %	90 %

6. SUMMARY

It has been shown that global statistical features in the pressure signals of handwritten samples contain important information as to the structure of the sample and to behavioral characteristics associated with the human individual. The combination of text-specific effects and user-specific traits encodes the pressure signal of any handwritten symbol or text. Therefore, authentication of human individuals is equivalent to the decoding of specific features concealed in the gathered pressure signal. Basically, there is no need to use the private “signature” for authentication, because individual traits and topological information can equally well be extracted from just a few characters. However, our results suggest that maximum identification rates may be obtained if each user selects a short sequence of meaningful, easy-to-write and frequently used words, e.g. something like “good morning” or “hello sunshine”.

Our preliminary field trials were performed with pen prototypes of yet imperfect ergonomic design, and participants have not been accustomed to handle the pen properly. Therefore, a considerable percentage of collected data was affected through clenching or intermediate repositioning of the instrument. Despite of these adverse effects the results of our study are very convincing. We conclude that future improvements of the pen design and the extension to a software-engine for multimodal biometrics offers great chances for BiSP to become a professional tool for numerous biometric applications.

7. ACKNOWLEDGEMENTS

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