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Reduced Dynamic Time Warping for Handwriting Recognition Based on Multi-dimensional Time Series of a Novel Pen Device

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***Abstract*—**The purpose of this paper is to present a Dynamic Time Warping technique which reduces significantly the data processing time and memory size of multi-dimensional time series sampled by the biometric smart pen device BiSP. The acquisition device is a novel ballpoint pen equipped with a diversity of sensors for monitoring the kinematics and dynamics of handwriting movement. The DTW algorithm has been applied for time series analysis of five different sensor channels providing pressure, acceleration and tilt data of the pen generated during handwriting on a paper pad. But the standard DTW has processing time and memory space problems which limit its practical use for online handwriting recognition. To face with this problem the DTW has been applied to the sum of the five sensor signals after an adequate down-sampling of the data. Preliminary results have shown that processing time and memory size could significantly be reduced without deterioration of performance in single character and word recognition. Further excellent accuracy in recognition was achieved which is mainly due to the reduced dynamic time warping RDTW technique and a novel pen device BiSP.

***Keywords*—**Biometric character recognition, biometric person authentication, biometric smart pen BiSP, dynamic time warping DTW, online-handwriting recognition, multidimensional time series.

I. INTRODUCTION

IN the future alternatives to the keyboard, mouse or a touch sensitive screen are required as input devices for small and mobile units like notebooks, personal digital assistants (PDAs), cell phones or flash -memories (sticks).

A novel Biometric Smart Pen BiSP has been developed which is a ball pen like device for the online input of handwritten characters and words, drawings, gesture and cursor movements.

The acquisition device is equipped with a diversity of sensors for monitoring handwriting movement carried out on paper pad or free in air. Different to common tablet-based input devices, the data are sampled exclusively by the pen and transferred either by wired or wireless transmission technology. The software engine used in the smart pen system covers a broad range of multi-dimensional time-series analysis. Many software methods had been tested for feature extraction and classification: Neural Networks NNW, Hidden Markov Models HMM, Support Vector Machines SVM and its combination [2],[3], statistical methods [4],[5], discrete Wavelet Transformation DWT and Dynamic Time Warping DTW with its variants [6],[7].

Preliminary study work has shown promising results in biometric person authentication based on handwriting [2], [5], [6], in assessment of neuromotor features for analysing diseases and medication [8],[9] and in recognition of handwritten single characters and words [4],[6],[10]. Due to its user friendly design, specific sensors and particular software for fast data acquisition and evaluation the smart pen system inspires to multiple applications in human computer interaction, biometrics and medicine. For these applications the BiSP system is still far from perfect but has a high potential for further improvement in terms of sensor techniques and software methods.

In biometrics the emphasis of the development work is to design a novel two factor person authentication method where biometric person recognition is combined with handwritten PIN recognition. The purpose is to enhance the accuracy of authentication by using a similar strategy which was mentioned first in [4], [5]. The concept and principle procedure are the following:

In a first step the PIN word handwritten by its owner is recognized by a similarity match of dynamic time warped (DTW) time series or of biometric features extracted from the time series. With the PIN word which figures like a signature, the person (owner) is identified among a big population of enrolled persons. In a subsequent step the PIN code is recognized as a sequence of isolated single characters using a similarity match, now applied to the owner's specific time series or biometric features stored in a biometric data base. To add security the owner of the PIN code now is verified by inspecting a PIN code data base. It is obvious that online single character and PIN word recognition are essential parts of the biometric two factor person authentication.

The DTW analysis of multi-dimensional time series representing handwritten items can lead to a high computing time and memory size. To meet this problem a top down hierarchical matching and classification process is required for online authentication. At the first stage heavy down-sampled time series or global statistical features extracted from original time series are used for a fast similarity match between an unknown sample (query) and references (prototypes) of a large population. In the second stage a more detailed final matching and classification technique is applied to time series of a small set of best matched candidates (words, characters, persons) as selected by the pre-classification. A fast and efficient software method for the pre-classification on the scale of

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strongly compressed data used for person and handwriting recognition is described in [4],[5],[10]. DTW, HMM, NNW, etc., are among the refined matching techniques where DTW analysis of time series gets very attractive for online handwriting recognition [11], [12], [13].

This paper deals with the single character and PIN word recognition by applying DTW and its variants on five channel time series generated by BiSP during handwriting on a paper pad. The paper is organized as follows. In Section II the novel biomertric smart pen device BiSP used in the experiments for data acquisition is described. Section III briefly outlines the concept of speeding up dynamic time warping DTW of multi-dimensional time series. Then in Section IV preliminary results of the experimental work of evaluation are presented and discussed. Section V finally summarizes the major findings and highlights the prospects of application.

II. Biometric Smart Pen Device BiSP for Data Acquisition

A novel Biometric Smart Pen system "BiSP" developed in our group is superior to current pen or tablet based human computer input devices in many respects [1]. BiSP is a ballpoint pen system which allows the record and analysis of handwriting, drawing and gesture movements on a paper pad or free in air. For a comprehensive assessment of pen movement and fine motor features of hand and fingers, the device is equipped with a diversity of sensors measuring the acceleration and tilt angle of the pen, the grip forces of fingers holding the pen and the forces and vibration generated in the refill during writing or drawing on a pad. A prototype of the acquisition device BiSP employed in the experiments is shown in Fig. 1.

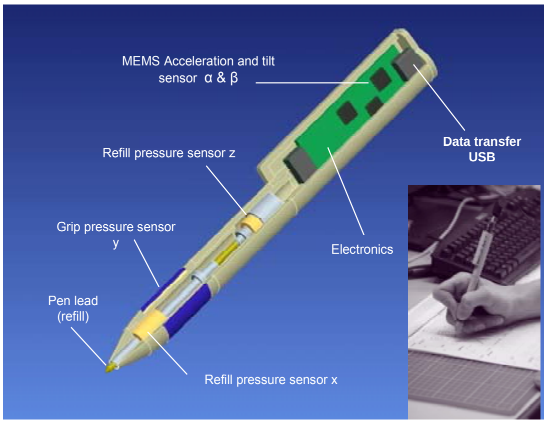

Fig. 1 BiSP prototype with 5 sensor-channels for monitoring handwriting movements

The change of forces resulting from handwriting on paper pad and transferred by the refill are monitored across (x & y) and longitudinal (z) to the refill axis by piezoelectric polymer films placed close to the front part and the end of the refill, respectively. The grip pressure of the fingers holding the pen is detected by a piezoelectric foil wrapped around the case of pen. The finger grip sensor makes its debut in the acquisition device.

A micro-electro-mechanical (MEMS) seismic sensor assembled inside the pen measures the acceleration and tilt of the device in three directions. The output signals are a superposition of both the acceleration and tilt detected by the inertial and gravitation effect, respectively. For biometrics there is no need to separate both physical values. In the case of handwriting on paper pad the sensor ultimately capture the tilt of the pen. The tilt itself is characterized by the angles α and β measured between the longitudinal axis of the pen and the vertical.

Altogether, the pen device provides five sensor signals low pass filtered and digitized by a 12 bit A/D converter at a sampling frequency of 500Hz. The digital data are transferred to a computer by a wired (HID-USB) or wireless low power (proprietary approach) transmission technology.

Typical time series recorded with BiSP during handwriting the single character "ü" are shown in Fig. 2.

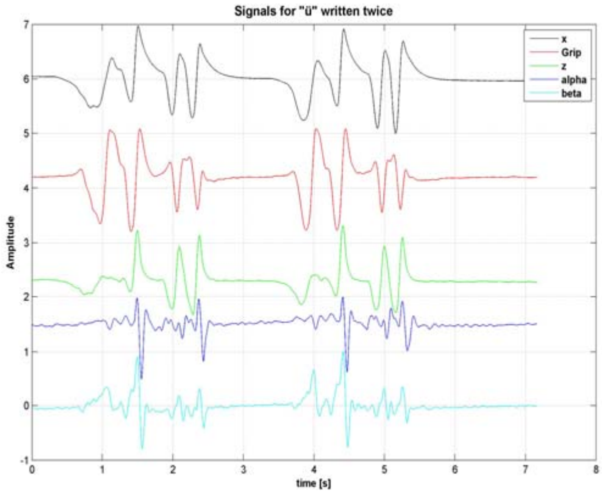

Fig. 2 Typical output of five time series of 2 refill pressure, 1 grip pressure & 2 tilt angles recorded with BiSP during handwriting twice the character ü

The characteristics features of the time series are essentially determined by the type of written item and by the fine motor movements of the writing person. They have to comply with the fundamental prerequisite for handwriting and person recognition: high reproducibility irrespective of the type of written items let it be a character, word or the individual pin, and high distinctiveness in order to discriminate between various human individuals or written items. An example for great similarities between repeated sensor signals (letter "ü", same person) or otherwise, pronounced differences (of different letters or writers) is depicted in Fig. 2 and 4, respectively.

DTW algorithm is applied for time series analysis of five different sensor channels providing pressure, acceleration and tilt data during handwriting on a paper pad.

III. Dynamic Time Warping Classifier

Dynamic Time Warping DTW is known to be useful for classifying single characters or words based on a similarity match of time series. One of the advantages of DTW is that it is able to match two time series $S = (s_1, s_2,\ldots\ldots s_n)$ and $R = (r_1, r_2,\ldots\ldots r_m)$ of unequal length $n \neq m$. Further DTW based classification yields a high performance even for characters with a small string length. DTW measures the similarity of two time series (S, R) in terms of the distance between S and R after they have been warped together. The value is found by minimizing a cumulative cost which is defined by the Euclidean distances between all matches (s_i, r_j).Given an unknown sample S, the DTW based classifier calculates the distances to all references R among a population (persons, characters, etc.), sorts them by distance, and returns a list of nearest references. The minimum-distance of the top best match decides for classification. The description of DTW is necessarily brief. For more details see [14], [15], [18].

Due to the quadratic time and space complexity O(nm) standard DTW has computing time and memory space problems, which limit its practical use especially in online handwriting recognition. To face with this problem there are some approaches to speed up DTW as described in [16], [17]. The computing time is reduced by confining the DTW match (1) to a few single characters handwritten by a small group of persons, (2) to down-sampled time series and (3) to the sum of the multi-dimensional time series. For clarity the DTW-algorithm is termed "Single DTW" (denoted SDTW) when applied to the time series channel by channel and "Reduced DTW "(denoted RDTW), when applied to the time series given by the sum of all sensor channels. The aim is to compare the performance of single character recognition based on RDTW and SDTW.

A. *Performance of Classification*

In the study work four criteria are established to judge the performance of classification: (a) the score of recognition (denoted by SR), (b) the certainty of best match (denoted by CM), (c) the runtime and, (d) the receiver operating characteristic ROC, which is common used for the evaluation of biometric person recognition.

For the recognition of a single character or pin written by one person the score of recognition SR (%) is defined as follows:

$$SR = \frac{G - falscount}{G} 100 \text{ with } G = C \cdot R \cdot (C-1)$$

where G is the number of all classification tests, C is the number of characters enrolled, R is the number of references for an item written by one person. The total number of incorrect or false classifications "*falscount*" is given by

$$falscount = \sum_{k=1}^{C} falscount_k$$

where "$falscount_k$" is the number of false classifications of character 'k' among the items and is determined by

$$falscount_k = \sum_{j=1}^{R} \sum_{i=1}^{C-1} f(d_{1,j}, d_{i+1,j})$$

where the DTW distance value $d_{1,j}$ stays for the top best match of character 'k' and the distance $d_{i+1,j}$ for the other characters ($i \neq k$).

The classification function f(,) used above is defined as:

$$f(a, b) = \begin{cases} 0 & if \quad a < b \\ 1 & \quad a \geq b \end{cases}$$

where 'a' and 'b' are two DTW distance values.

Note: the DTW distances $\{d_{u,v}\}$ of character 'k' comes from queries (of character 'k') matched to all references of all characters. The indices 'u' and 'v' refer to characters and queries, respectively.

Further the term "false classification" means the query sample and the top best matching reference sample do not represent the same item.

The certainty of best match CM is defined by:

$$CM = 100x(d_d - d_t)/ d_t,$$

where 'd_t' stays for the DTW distance between the query and a reference sample with the top best match representing the same person and item, while 'd_d' is the distance of the best match between query and a reference representing different items. A high value of CM means a high certainty of classification.

The run time is a critical parameter in real time recognition systems. Therefore the aim is to minimize the computing time for single item recognition without degrading SR and CM significantly.

Receiver Operating Characteristic ROC of a biometric classification system is a graphical depiction of the relationship between the False Rejection Rate FRR and False Acceptance Rate FAR as a function of the decision threshold's value. The area under the ROC curve AUC with ≤ 1 is a well suited measure to evaluate the performance of recognition. The better the performance, the greater the area under the ROC curve. For more details of ROC in biometric person recognition see [19].

IV. Experiments and Results

The main objectives of the experiments were a critical validation of RDTW applied on time series provided by the BiSP acquisition device, and to evaluate down-sampling effect on the performance of single character and PIN word recognition.

A. *Database*

The database used in the experiments is collected from 10 different persons writing items with the BiSP device on a paper pad. Each item was written ten times in sequence by a person under optimal condition. 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 consists of eleven single characters {letters A, B, E, M, ü, digits 0, 4, 5, 7, two symbols % □} and a set of 10 different PIN words. The unique PIN word is a sequence of seven randomly selected single characters timely spaced written by the owner of the PIN (e.g. "4MBE%A7").

The corresponding data base covers (10 entries per item)x(10 writers) = 100 samples for each enrolled item. Each entry of an item is represented by a set of five time series.

For the evaluation task the data base is subdivided in query (test) and reference (prototype) samples.

B. Preprocessing of Multi-Dimensional Time Series

The DTW match was performed after an adequate preprocessing of the original signal data. The time series are smoothed, down-sampled, segmented and normalized without discarding valuable information.

Smoothing: Smoothing of the data based on local regression using weighted linear least squares and a 2nd degree polynomial model is used to eliminate potential sensor noise.

Segmentation: All character items are written and sampled separately so, that no segmentation of signals is required.

Normalization: In order to compensate partly large variations in amplitude of signals normalization of all data from handwritten characters is done to rescale to [-1 1].

Down-sampling: Down-sampling by low pass filtering sensor signals is usually done to reduce the data rate or, equivalently, the size of the data. It is an efficient way to shorten the runtime of recognition as the complexity of DTW matching depends quadratically on the number of data points.

Data processing and DTW implemented in MATLAB [20] was done by using a computer with a Pentium 4 processor (2, 4 GHz, 3 GB RAM).

C. Sum of Multi-Dimensional Time Series

For each handwritten item the BiSP device provides five time series corresponding to five sensor channels as shown in Fig 2.

In order to evaluate the SDTW and RDTW techniques the DTW algorithm is applied to the data of each channel and to the data obtained from the sum of all channels, respectively.

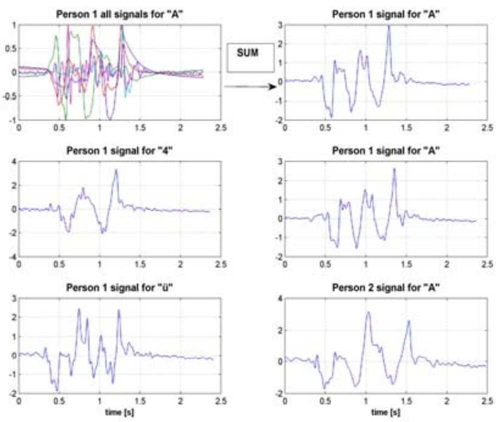

Fig. 3 Time series obtained by the sum of five sensor channels. The signals are from the items A, ü and 4 written by two persons

Thus the SDTW match provides five distance values "d_k" for a written item. To calculate the criteria of performance "SR, CM and AUC" the algebraic mean of all d_k's is used. The drawback of SDTW is its large computing time. The recognition time of a written item can be significantly reduced by a factor of five using RDTW, because the time series of five channels are replaced by the sum of them. As shown in Fig. 3, the added channel signals reveals distinct dynamics and depict a high reproducibility and distinctiveness even though the dynamic attributes of all individual channels are included. It is obvious that enough specific biometric and object related information is embedded in even a time series of short length.

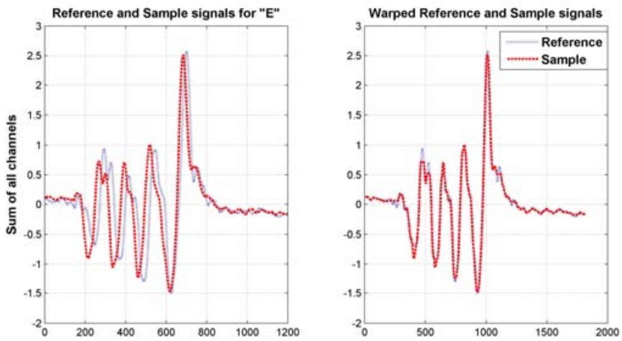

Fig. 4 Two time series of letter "E" written by one person before and after RDTW

For demonstration a RDTW match of two time series of the item "E" written by the same person is shown in Fig. 4. It indicates that equal items written in several copies by the same person are matched very well (reproducibility), i.e. the RDW-distance is very low.

It was also shown that different items written by the same person or equal items written by different persons are sufficiently dissimilar (uniqueness) and have an obvious larger RDTW-distance. For an example the letters "A" repeatedly written by the same person have a lower distance (0.015) and, in contrast, higher distance for "A" written by different persons (0.033) or "A "and "4" written by the same person (0.027). The distance of RDTW, obtained from the DTW match between the appropriate time series is an excellent quantitative measure for similarity and dissimilarity of written items. The RDTW is well suited to classify (discriminate) between human individuals or items among the reference population and to speed up the computing time in single character recognition. For an evaluation of RDTW we investigated the performance parameters of single character and PIN word recognition.

D. Single Character Recognition

For single character recognition one query out of all samples is repeatedly selected corresponding to one of all characters written 10 times by the same person and is compared against the remaining set of (110-1 queries per character) x 10(entries per character) x 11 (characters) = 11990 samples. The intra-individual match was accomplished for all enrolled persons. Based on the SDTW and RDTW similarity match the performance parameters are calculated in terms of SR, CM and runtime for the recognition of eleven single characters. The values in Table I are obtained from data down-sampled by M=10. In addition the values are writer independent that is an average of all enrolled persons.

TABLE I
WRITER INDEPENDENT PERFORMANCE OF SINGLE CHARACTER RECOGNITION FOR SDTW AND RDTW OF DOWN SAMPLED DATA (M=10)

items	Score of recognition SR		Certainty of best match CM		Runtime (s)	
	SDTW	RDTW	SDTW	RDTW	SDTW	RDTW
0	99.90	99.50	56.54	79.81	1.75	0.36
4	99.80	98	41.66	31.86	1.84	0.37
5	99	98.50	29.45	30.19	1.89	0.38
7	99.50	98.60	27.58	34.44	1.82	0.37
A	99.70	99.10	35.68	30.32	1.95	0.39
B	100	99.30	37.68	46.44	1.93	0.39
E	99.80	99.60	36.90	53.11	1.99	0.40
M	99.30	99.20	34.05	41.56	1.99	0.39
ü	100	100	49.03	58.34	2.0	0.41
%	100	99.70	49.03	61.91	2.1	0.43
□	100	100	57.72	77.37	2.18	0.44
Avg	99.72	99.22	41.39	49.58	1.94	0.39

The recognition score SR is slightly higher (on average 0.5%) when SDTW is applied but RDTW provides a higher certainty of match CM (about 20%). A further benefit of RDTW is its lower computing time, which is about the fifth part of the SDTW time. The performance of the RDTW method complies very well with the claims of an online single character recognition system. If RDTW is applied to BiSP signals down-sampled by M=10 single characters, handwritten by the same person can be recognized at an excellent score (algebraic mean of all characters is better 99%) with a responds time of less than 0.5 seconds. The score values ≥ 99% indicate that the short length of a single character encodes an amazing amount of person and item specific information.

In the following the receiver operating characteristic ROC is applied for evaluation, because it is common used for judging recognition systems. Typical ROC curves of single character recognition are shown in Fig. 5 comparing the performance of SDTW and RDTW.

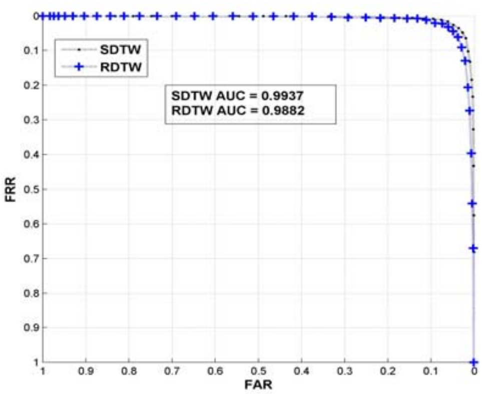

Fig. 5 ROC curves for person-specific single character recognition based on SDTW and RDTW

The ROC curves are very smooth and the areas under the curve (AUC≥0.988) indicate an excellent grade of performance of single character recognition.

The results are superior to the state of the art of online single character recognition using pen or tablet based devices [7],[10],[12],[13]. This mainly reveals the high quality of the BiSP signals used for DTW.

E. PIN Word Recognition

An issue of the study work was to compare the performance of PIN word with single character recognition. For evaluation, the procedure of the DTW based recognition of a PIN word written by the owner is the same as used for single characters. Table II shows the performance parameters of single character and PIN word recognition.

TABLE II
PIN WORD RECOGNITION IN COMPARISON TO SINGLE CHARACTER RECOGNITION. THE PERFORMANCE AVERAGE FOR M=10

items	SR SDTW/ RDTW	CM SDTW/ RDTW	Runtime SDTW/ RDTW	AUC SDTW/ RDTW
Single char	99.72/ 99.22	41.39/ 49.58	1.94/ 0.39	0.994/ 0.988
Pins	100/ 100	93.25/ 120.22	19.87/ 4.05	1.0/ 0.998

The values of SR, CM and AUC of a PIN word are slightly greater than that of single characters due to the longer time series. But the computing time (20 sec for M=10) needed to recognize a PIN word among its population is far too much for an online recognition system. This runtime can increase considerably with the amount of enrolled PIN words or persons. To cope with this problem the advantage of a higher degree of dawn-sampling (see chapter 4.6), is taken or to restrict on single character recognition. In the latter case the responds time of PIN recognition should not be more than 1 second, provided that the single characters are recognized during writing the PIN.

F. Down-Sampling of Time Series

To illustrate the effect of down-sampling on the performance of score of recognition, CM and the runtime of single character and PIN word recognition were determined in dependence on the down-sampling factor M. The values of M are adjusted by filter techniques implemented in MATLAB [20]. For example, the down-sampling factor of M=10 was achieved using the Chebyshev 8th order low pass filter with a cut-off frequency of about 20 Hz.

As shown in Table III, for single character recognition the increase of down-sampling reduces the runtime considerably whereas the score of recognition SR decreases slowly. Down-sampling up to M=20 shorten the time of RDTW by a factor of about 10 down to 0.16sec and decreases the score by less than 0.5%. The down-sampling effect on the performance of PIN word recognition is represented in Table IV. It indicates that PIN word recognition allows a heavy down-sampling without a rigorous degradation of score values. For RDTW a runtime below 0.5sec and a score SR of 99% can be achieved when the sample data are compressed by M =40.

Due to the results in Tables III and IV, it is concluded that single character and PIN word recognition can be performed in a time saving hierarchical DTW match. First DTW is applied on heavy down-sampled data (e.g. M= 50 or more) to select a small set of best matched references. In a second stage DTW is used to match the low down-sampled data of the preclassified references (e.g. M=10 or less).

TABLE III
THE EFFECT OF DOWN-SAMPLING M ON THE AVERAGE SCORE SR, CERTAINTY CM AND RUNTIME OF SINGLE CHARACTER RECOGNITION. THE AVERAGE VALUES ARE WRITER AND CHARACTER INDEPENDENT

M	Score SR		Certainty CM		Runtime (s)	
	SDTW	RDTW	SDTW	RDTW	SDTW	RDTW
4	99.83	99.31	66.70	68.23	8.06	1.64
6	99.77	99.29	52.48	58.33	4.03	0.83
10	99.72	99.22	41.39	49.58	1.94	0.39
16	99.50	98.99	32.53	44.59	1.05	0.21
20	99.30	98.82	30.56	44.22	0.79	0.16
30	98.79	97.58	26.27	41.03	0.51	0.10
40	97.72	96.80	26.58	41.05	0.38	0.08
50	97.0	95.04	25.58	38.94	0.31	0.062
60	95.80	94.82	25.07	38.90	0.26	0.052
70	95.51	92.89	24.73	38.23	0.23	0.048
80	93.79	92.15	23.71	37.79	0.20	0.042
90	91.87	90.10	21.70	38.66	0.19	0.038
100	92.95	89.27	24.30	38.08	0.17	0.035

TABLE IV
THE EFFECT OF DOWN-SAMPLING M ON THE PERFORMANCE OF PIN WORD RECOGNITION AMONG A POPULATION OF 10. THE VALUES ARE AVERAGED OVER ALL PINS

M	Score SR		Certainty CM		Runtime (s)	
	SDTW	RDTW	SDTW	RDTW	SDTW	RDTW
6	100	100	124.81	153.72	51.87	10.63
10	100	100	93.25	120.22	19.87	4.05
16	100	100	57.72	82.66	8.43	1.72
20	99.44	100	38.27	64.30	5.61	1.15
30	99.44	99.88	20.29	40.89	2.90	0.59
40	97.44	98.77	15.63	28.66	1.95	0.39
50	96.88	98.66	15.05	22.25	1.44	0.28
60	96.77	98.77	13.91	20.68	1.15	0.22
70	94.88	98.66	12.03	18.22	0.92	0.19
80	93.66	98.11	10.86	17.44	0.79	0.16
90	94.33	96.11	11.04	19.02	0.69	0.14
100	94.0	95.11	11.69	19.62	0.61	0.12

V. CONCLUSION

It is found that the RDTW technique applied to down-sampled BiSP data is well suited to classify between human individuals and handwritten items like PIN words or just a short sequence of isolated characters. The performance of the RDTW method complies very well with the claims of an online recognition system. Single characters and PIN words, handwritten by the same person can be recognized at an extremely high score (better 99%) with a responds time of less than 0.5 seconds. These excellent results lead to a promising application, namely the biometric recognition of PIN codes being an essential part of the biometric two factor person authentication method, where biometric person and PIN code recognition is combined. To cope with the computing time problem in character recognition of large population RDTW will be applied in a hierarchical classification scheme: First RDTW is applied on heavy down-sampled data providing a fast pre-classification among a large population. In a subsequent step, it follows a more detailed final classification by applying RDTW on a small set of low down-sampled data selected by the pre-classification. This procedure is expected to be an effective approach to reduce the computing time without a pronounced degradation of performance.

In combination with RDTW technique developed for fast matching of multi-dimensional time series the BiSP device becomes an innovative system for widespread use not only in handwriting and biometric person recognition but also in medical areas. According to the implemented DTW classification algorithm, the BiSP system can be utilized for the classification and quantification of hand-motor dysfunctions and the analysis of fine motor movements of patients under drug treatment.

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