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Use of random time-intervals (RTIs) generation for biometric verification

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ABSTRACT

We explore the possibility of using human-generated time-series as biometric signature. Adopting a simple psychometric procedure, in which a button is pressed in entirely random manner, successive elapsed times are registered and gathered in a signal reflecting user's internal cognitive processes. By reconstructing and comparing the dynamics across repetitions from the same subject a noticeable consistency was observed. Moreover, the dynamics showed a prominent idiosyncratic character when realizations from different subjects were contrasted. We established an appropriate similarity measure to systematize such comparisons and experimentally verified that it is feasible to restore someone's identity from RTI (random time-interval) signals. By incorporating it in an SVM-based verification system, which was trained and tested using a medium sized dataset (from 40 persons), a considerably low *equal error rate* (EER) of ∼5% was achieved. RTI signals can be collected effortlessly and this makes our approach appealing, especially in transactions mediated by standard pc terminal keyboards or even telephone keypads.

1. Introduction

The new era of Biometrics includes automated methods of recognizing a person based on a physiological or behavioral characteristic, like face, fingerprints, hand geometry, handwriting, iris, vein topography, and voice [1]. As the level of security breaches and transaction fraud increases, the need for highly secure identification and personal verification technologies is becoming apparent. Biometric-based solutions are able to provide for confidential financial transactions and personal data privacy. Utilizing biometrics for personal authentication is becoming convenient and considerably more accurate than current methods (such as the utilization of passwords or PINs). This is because biometrics links the event to a particular individual (a password or token may be used by someone other than the authorized user), is convenient (nothing to carry or remember), accurate (it provides for positive authentication), can provide an audit trail and is becoming socially acceptable and cost effective.

After the first wave of biometrics, which included static and naturally distinctive characteristics like the face and signature, researchers started to experiment with more dynamic characteristics like the voice or handwriting style (online/dynamic signature verification) which are more difficult to be imitated (e.g. [2]). Keystroke dynamics [3] also known as typing recognition, is a typical biometric approach of this kind. It analyses the way a person types. Users enroll by typing the same word or phrase a number of times [4]. Verification is based on the concept that the rhythm with which a person types is distinctive. It is an appealing approach since no extra hardware is required and typing is the most natural way for a user/client to interact with the system/server in most applications, particularly over the world-wide web. However, the passage to be typed might need to be fixed and this means a memory load, analogous to remembering an extra password. Moreover, there is a potential change due to continuous practice of the same typing patterns.

In the present paper we propose an alternative biometric in which the simplicity of interface is kept, while the restriction of typing specific patterns is alleviated. The present work was motivated by recent, independent studies in cognitive neuroscience and psychiatry reporting that the generation of random rhythms or numbers is a demanding cognitive task and carries enough information to discriminate between different clinical populations. When someone is asked to generate (verbally of via keyboard) random numbers, there is a cognitive load implied, since there is a close interaction between short-term memory and internalized decision making mechanisms [5–8]. A closely related task is the generation of random tapping rhythms [9,10]. Finger tapping, in particular, requires sensorimotor interaction and specific cortical networks responsible for this have been identified and modeled by Kelso [11,12]. Interestingly, it has been demonstrated that everyone has his own eigen-rhythms regulating spontaneous finger tapping [13].

Following a standard psychometric procedure [14–16], we gathered multiple RTI (random time-interval)-signals from a random

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group of subjects and systematize the inter-subject comparisons with respect to the dynamics governed the generation of the registered random-rhythms. Due to the non-stationary (and rather 'chaotic') character of the signals, neither standard spectral analysis nor traditional morphological analysis could provide us with useful discriminating characteristics. Nonlinear-dynamics, instead, enabled us to compare the underlying generation mechanisms directly based on the time-series (TS). Dynamic trajectories, when suitably reconstructed, were proved sufficient for building reliable biometric-tests.

The contribution of our paper is twofold. At an experimental level, it is the first time that human-generated TS of random latencies are tested as biometric. Moreover, at a more theoretical level, TS related to brain-event dynamics are compared in a novel way, namely by means of a non-parametric statistical test. The results from the extensive experimentation with a particular authentication-system (encompassing the introduced ideas) are highly encouraging, since the measured performance approximates the current standards in the field, without resorting to highly sophisticated registration procedures (like 3D scanners).

The paper is organized as follows. Section 2, describes the procedure for recording RTI-signals. Section 3 is devoted to the novel pairwise comparison of such signals. Section 4 describes a possible way to transform these pairwise comparisons to discriminant-functions. Section 5 outlines a specific verification system, while Section 6 includes a detailed evaluation. The final section includes a short discussion and some comments on a more beneficial implementation of our suggested-methodology.

2. The random rhythm generation test

The procedure for generating the RTI signals is very simple [14–16]. The subject is asked to press the space key of the computer with the index finger of his/her dominant hand as irregularly as possible, until the screen shows the end of the exercise. The first time the subject encounters this task, he/she is provided beforehand with an example consisting of a square 4×4 cm, which appears and disappears in the screen at random rhythm and is synchronized with a sequence of beeps. The particular example is indicative of the sort of TS he has to create and—as it is explicitly stated—its exact reproduction is not the objective of the task. If $x(t)$ denotes the T-length sequence of exact time-latencies of subject's blows $\chi[n]=[t_1,t_2,\ldots,t_T]$, the corresponding RTI signal takes the form $x[n]=[t_2-t_1,t_3-t_2,\ldots,t_T-t_{T-1}]$. During the enrolment-stage, such a $\chi[n]$ sequence is provided by the user and the RTI signal (i.e. the sequence of latency-differences) is automatically created and compared with analogous ones previously stored in the database of the system. This comparison should reflect as much as possible the inter-user differences regarding the internalized process of generating random rhythms. On the other hand, someone's mechanism was expected to remain the same and this constancy should be apparent, as well, in the temporal characteristics of his RTI-signals measured repeatedly. Fig. 1a, includes a few examples of RTI-signals recorded from three different subjects.

3. Comparing the reconstructed dynamics

Since, the ultimate goal was to contrast the underling dynamics by means of comparing the corresponding TS, we resorted to techniques from nonlinear dynamics field [17]. In our approach we, first, reconstruct the dynamics from each TS as a trajectory in a suitable chosen state-space of high dimensions and then compare these trajectories—in pairs—via a powerful non-parametric multivariate-statistical test [18,19].

Using Taken's *time-delay embedding* procedure [20], a succession of delay-vectors $\mathbf{x_i}(n)=(x[n-(p-1)\times\tau],\ldots,x[n-\tau],x[n])$ is first formed from each RTI-signal $x_i[n]$ and them listed in a matrix $\mathbf{X}=[\ldots\mathbf{x_i}(n-1)|\mathbf{x_i}(n)|\mathbf{x_i}(n+1),\ldots]$. In this formulation the parameter p is the *embedding dimension*, i.e. the dimensionality of reconstructed state-space and τ is the so-called *time-lag* parameter [17]. The former is usually selected high enough so that the degrees of freedom of the dynamical system are preserved. The latter is usually defined so as to decorrelate the successive components of the formed vectors. The matrix $\mathbf{X}$ tabulates the dynamical orbit related with the generation mechanism of the RTI-signal. Fig. 1b, demonstrates two such trajectories reconstructed (with $\tau=5$ and $p=2$) from RTI-signals of Fig. 1a. The systematic comparison between any two such trajectories $\mathbf{X}$ and $\mathbf{Y}$ resulting from time-delay embedding is a relative unexplored task and only recently a few methodologies have been introduced [21–24]. Motivated by our own previous work, where we had compared trajectories related to brain-response dynamics [25,26], we adopted the statistical procedure of multivariate Wald-Wolfowitz (WW-test) which is described in some detail in Appendix B. In short, using two sets of delay-vectors $\{\mathbf{x_i}\}$ and $\{\mathbf{y_i}\}$ (tabulated correspondingly in matrices $\mathbf{X}$ and $\mathbf{Y}$) the overall *minimal spanning tree* (MST) graph is constructed (see Appendix A) and the W statistic quantifies if the different branches of MST are populated equally by the two sets of vectors. W is computed based on the encountered combinatorics and used as a measure expressing the similarity between the dynamics of RTI-signals $x[n]$ and $y[n]$. The more positive the value $W(x[n],y[n],\tau,p)=W(\{\mathbf{x_i}\},\{\mathbf{y_i}\})$, the more similar the two trajectories are. The function of WW-test is demonstrated in details via Fig. 1c, where RTI-signals from two different subjects are contrasted. It is clear that WW-test practically takes into account the relative overlap of the corresponding trajectories. Hence the W-index is a symmetric measure, i.e. $W(x[n],y[n],\tau,p)=W(y[n],x[n],\tau,p)$. Due to the non-parametric character of the employed test, this index has a generic character when used as a similarity measure for comparing the dynamics from two different TSs. The only restriction is that the embedding parameters p and τ should be the same for the two signals. It can easily be understood that WW-test can compare signals of different length and simultaneously ignore differences due to relative latency jitter (i.e. it is translation invariant). Moreover, since the W-index springs from an appropriate standardization (see Eq. (B.3)), it carries an absolute meaning and, hence, can be compared across different embeddings of the same RTI-signals. This particular option can be utilized, as it described below, to optimize the selection of the two involved parameters (τ, p).

4. Classifying the reconstructed dynamics and optimizing the embedding

Having introduced the similarity measure $W(x[n],y[n],\tau,p)$ between any two RTI-signals $x[n]$ and $y[n]$, we proceed by describing the way the adopted similarity measure can be utilized in establishing classifiers, the core-machinery in any biometric-system. For a given set of available RTI-signals $x_i[n]$, $i=1,\ldots,N$ with known identity, we compute all pairwise similarities and tabulate them, after a simple transformation, in an $[N\times N]$ distance-matrix $\mathbf{D}$ with elements

$$[D]_{i,j}=D(i,j)=\begin{cases}0 & W(x_i[n],x_j[n],\tau,p)>0\\ \mathrm{abs}(W(x_i[n],x_j[n],\tau,p)), & \text{otherwise}\end{cases} \quad (1)$$

Since the majority of classifiers operate on vectorial data, the above relational data are transformed to coordinate vectors via multidimensional scaling (MDS), a spectral technique that results to N vectors $g_i\in R^l$ such that the interpoint Euclidean distances $\|g_i-g_j\|$ approximates as much as possible the tabulated ones $[D]_{i,j}$. The MDS operation is signified as $\mathbf{G}=\mathrm{MDS}(\mathbf{D},l)$, with l denoting the output