A Sensing Seat for Human Authentication

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***Abstract*—This work is focused on the design and the realization of a sensing seat system for human authentication. Such a system may be used for security purposes in trucks, cars, offices, and scenarios where human subject authentication is needed and a seat is available. The sensing seat is realized by a seat coated with a removable Lycra sensing cover equipped with a piezoresistive sensor network. Since each sensor consists of a conductive elastomer composite rubber screen printed onto a cotton Lycra fabric, the sensing cover is able to respond to simultaneous deformations in different areas. This technology avoids the use of rigid electronic components and enables the realization of different cover layouts according to different types of seats. The algorithms for the enrollment, authentication, and monitoring tasks are discussed. A measurement campaign was carried out using data from 40 human subjects. The authentication capabilities of the system are reported in terms of acceptance and rejection rates, showing a high degree of correct classification.**

***Index Terms*—Human authentication, security, sensing seat, strain sensor.**

I. Introduction

SEVERAL companies are currently working to realize comfortable interactive seats. These systems, some of them already on the market [1]–[4], use different technologies and materials, but they share the use of sensors that measure the pressure exerted on the seat by the passenger. Actually, the existing sensing seats are not able to perform the human authentication task and no result on this topic, even if in a preliminary stage, was found in literature review. Indeed the sensor technology used in such existing systems is not adequate to perform the authentication task. In order to detect and correctly classify the human profile signature, many sensors should be used and the hardware architecture would result in a complex and delicate system. The authors decided to adopt a novel strain sensor technology in order to realize a versatile sensing seat able to address the human authentication task. In this work, the authors show the design and realization of an unobtrusive and versatile sensing seat system for human authentication that can be employed in different scenarios such as truck and car pilots, airplane pilots, plant and office personnel, and, in general, environments where the security is mandatory and a soft seat is available.

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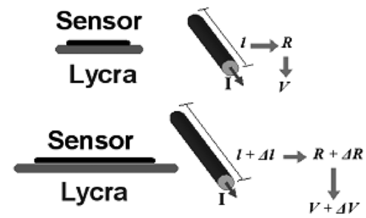

Fig. 1. Transduction principle of the CE strain sensor.

The proposed system, as part of the Human Monitoring and Authentication Using Biodynamic Indicators and Behavioral Analysis (HUMABIO) project for multimodal human authentication [5], is currently being tested in truck and office pilots. HUMABIO is an EC cofunded Specific Targeted Research Project (STREP) where new types of biometrics are combined with state-of-the-art sensor technologies in order to enhance security in a wide spectrum of applications like transportation safety and continuous authentication in safety critical environments like laboratories, airports, or other buildings.

II. Sensing System

The sensing seat system is realized by a sensing cover placed between the seat and an external cover that shields the sensing layer from the environment. The sensing cover is equipped with several strain sensors [conductive elastomers (CEs)] grouped in several patches. The noncommercial sensors [6] used for this application are developed at the laboratories of the University of Pisa and they allow piezoresistive sensing fabrics to be realized [7]. The sensors are realized by means of CE composites that show piezoresistive properties when a deformation is applied (Fig. 1). In order to develop strain sensors, they can be integrated into fabric or other flexible substrates. The CE we used is based on a WACKER Ltd product (Elastosil LR 3162 A/B). It consists of a mixture of graphite and silicon rubber. WACKER Ltd guarantees the nontoxicity of the product.

Strain impulses applied to a CE sensor result in a typical differential voltage behavior, shown in Fig. 2. Sensor response shows a peak in correspondence to every mechanical transition. Sensor responses during constant pressure time intervals may be approximated by decreasing exponential, assuming the local minimum as the steady-state value. The longer the pressure time interval, the more the above mentioned approximation is accurate. In order to remove the contribution of high order exponential, the first-order time constants were extracted by means of a window filter. This choice allowed quantization errors introduced by the acquisition device in response to rapid transitions to be avoided and sensor steady-state deformation, related to slower frequency components, to be maintained.

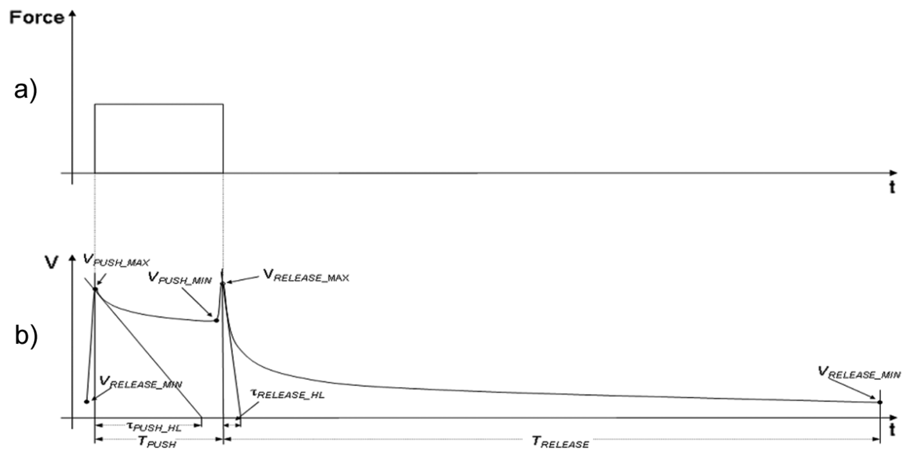

Fig. 2. Strain sensor voltage signal and extracted features (b) in response to a strain impulse (a).

TABLE I
CORRESPONDENCE BETWEEN THE CE STRAIN SENSOR AND THE ELECTRIC MODEL FEATURES

Feature of the variation of the sensor resistance	**Feature of the variation of the charging/discharging currents of the circuit**	**Symbol**
Initial peak $[k\Omega]$	Initial peak $[A]$	$I_1(0)$
Steady-state value for the deformation phase $[k\Omega]$	Steady-state value for the charging phase $[A]$	$I_1(\infty)$
Time constant of the first-order exponential components for the deformation phase $[s]$	Time constant for the charging phase $[s]$	τ_1
Time constant of the first-order exponential components for the release phase $[s]$	Time constant for the discharging phase $[s]$	τ_2

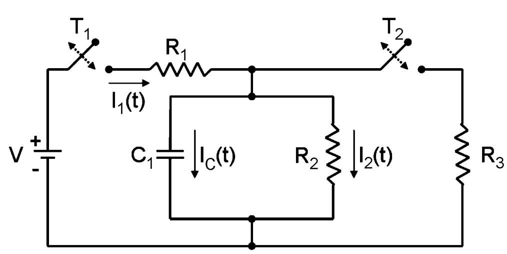

Fig. 3. Electric model of a CE strain sensor.

Taking into account the first-order components of the sensor response (resistance variation) to a rectangular stimulation (applied deformation), the equivalent circuit represented in Fig. 3 can be derived.

The power supply V is the electrical equivalent of the imposed deformation. The switch $T1$ (initially open) is closed and opened in correspondence to the beginning and the end of the imposed deformation, respectively. The switch $T2$ (initially open) is closed when $T1$ is opened again. Following a simple analysis of this circuit, it is easy to recognize that the variation of the charging and discharging currents of the capacitance in consecutive phases of stimulation are equivalent to the variation of the resistance of the sensor during its deformation and the following release, respectively. The circuit parameters $R1$, $R2$, $R3$, and C can be derived by using the features, extracted from reference experimental signals, listed in Table I.

A circuit voltage of 1 V was assumed as the equivalent of a deformation of 1 mm, while a circuit current of 1 A was assumed to correspond to a variation of the sensor resistance of 1 kΩ. Values of the features listed above were extracted from ten cycles of a reference experimental signal and were used to derive the circuit parameters by means of the following system of equations:

$$\begin{cases} \tau_1 = C(R_1 \| R_2) \\ I_1(0) = \frac{V}{R_1} \\ I_1(\infty) = \frac{V}{R_1+R_2} \\ \tau_2 = C(R_2 \| R_3). \end{cases}$$

According to these ten cycles of stimulation, the solution of this system provided the results reported in Fig. 4, showing the time constants τ_1 and τ_2 have values of the order of 1 s.

The sensing cover consists of several arrays of strain sensors directly printed onto a Lycra tissue. The overall design results in a high-impedance circuitry where a reference current is injected. The high-impedance characteristic allows both sensors and wires to be realized by means of the same technology and to gain unobtrusivity. Indeed, the use of common electrical wires is avoided within the sensing cover. Moreover, the power consumption is near zero resulting in a completely safe system. A connector plug is placed in one side of the sensing cover in order to connect the system to the front-end module. The fabric

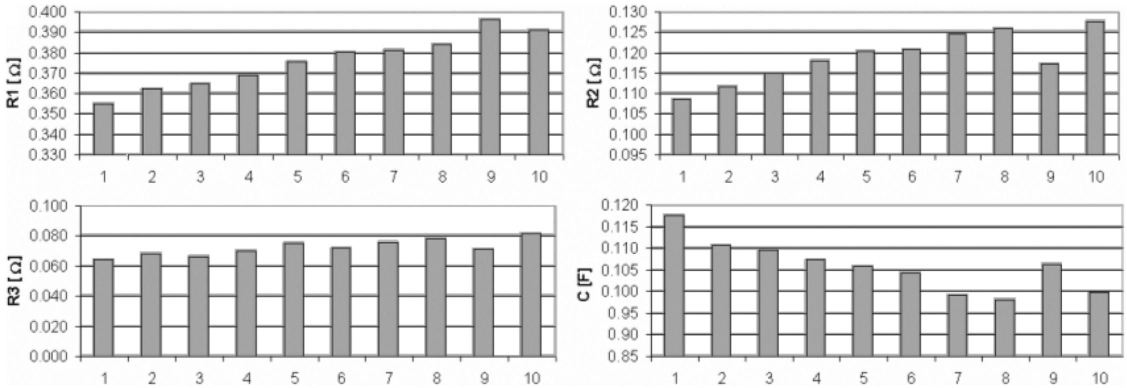

Fig. 4. Values of the parameters of the equivalent electric model extracted from ten cycles of a reference experimental signal.

a) b) c)

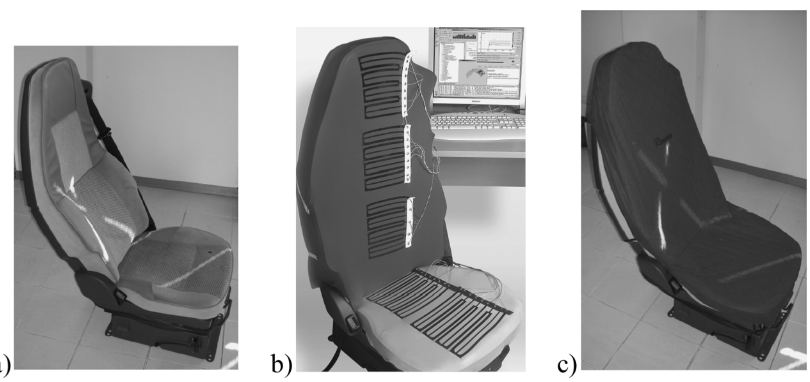

Fig. 5. Sensing seat system. (a) The truck seat. (b) The truck seat equipped with the sensing cover. (c) The truck seat equipped with the sensing cover and with the external cover.

equipped with distributed and redundant unobtrusive strain sensors guarantees to address plasticity, low dimension, lightness, and low cost. Since the strain sensors can be directly printed on the fabric, specific cover layouts may be designed to coat different seat shapes obtaining a good adherence to the seat. As a result, the sensing seat system does not interfere with the mechanical structure of the seat and it is designed as an extension of the seat itself (Fig. 5).

Several topology layouts were taken into account (series, parallel, and quadrupole network of sensors) and finally the best compromise between the technical complexity and the classification performance of the system was found using the series network. The sensing cover prototype is equipped with 28 strain sensors distributed in 5 sensing patches. Each patch consists of a series strain sensor array that is driven independently by the front-end module. As it is shown in Fig. 5(b), two patches are placed on the bottom side of the sensing cover, while three patches are placed on the upper side.

The existing sensing cover prototype was tailored to a real truck seat belonging to a specific truck model. Different layouts could be developed to handle different types of seats (e.g., office seats, car seats). It should also be remarked that the seat must be soft enough to guarantee the sensors to be adequately stretched as a human subject is seated. Moreover, as it will be explained below, since the signals supplied by the sensors depend on the positioning and the initial stretching of the cover, data are consistent only after the cover is mounted over the specific seat (i.e., the enrolment signatures are no longer valid if the cover is dismounted and mounted again even on the same seat).

III. Data Acquisition System

A front-end device for the signal conditioning was designed and developed in order to guarantee the flow of data between the sensing cover module and the data acquisition board (DAQ). A 44-pin cable connects the sensing cover to the hardware front-end device that performs a signal conditioning for each strain sensor channel. The front-end device imposes a reference current for each patch of the sensing cover and sends the voltage information to a National Instruments NI-cDAQ-9172 DAQ. The DAQ is connected to the PC through the USB hub. Once the system is connected, the signals are acquired in real-time with a sampling rate equal to 100 Hz. As described below, the processing application runs asynchronously with respect to the data acquisition process.

During each measurement, the subject is seated onto the sensing seat system and is supposed to stay still for 5 s during the data acquisition process. As it will be discussed later, the system is also able to automatically establish if the user is still enough and, if not, then the measurement will be extended accordingly. As it is shown in Fig. 5(b), each strain sensor (black strip) is positioned horizontally and, as the user is seated, will supply a signal over time that is qualitatively represented in Fig. 2(b). The steady-state value is calculated from the T_{PUSH} time period and it represents the feature extracted from the

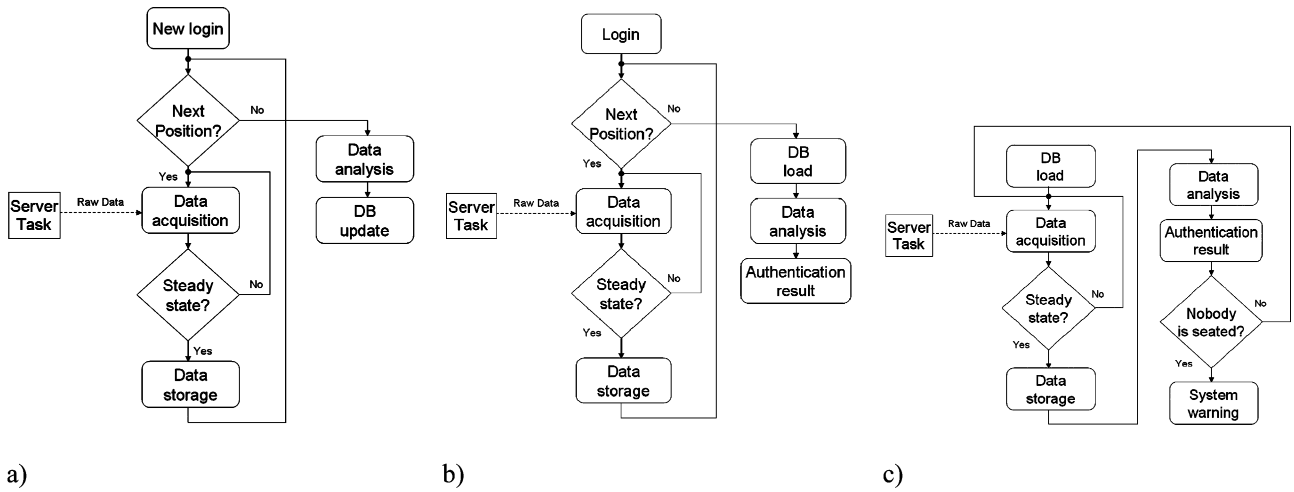

Fig. 6. Sensing seat system recording protocol. (a) Enrollment task; (b) authentication task; (c) monitoring task.

strain sensor signal. The first-order time-constant $\tau_{\mathrm{PUSH_{HL}}}$ assesses on a value of 1 s, so a few seconds are enough to estimate the steady-state value $V_{\mathrm{PUSH_{MIN}}}$. Since 28 strain sensors are used, the signature of each measurement consists of a 28-component voltage vector whose elements represent the steady-state value of each sensor. Since these elements are linked to the deformation of the sensors due to the subject pressure, each signature represents the one-dimensional deformation vector along the vertical axis of the seat. As a result, the voltage vectors available for each measurement and for each predefined position are related to the pressure exerted by the subject on the seat [8]–[10]. In this work, the steady-state voltage vectors are used as a biometric signature of the subject.

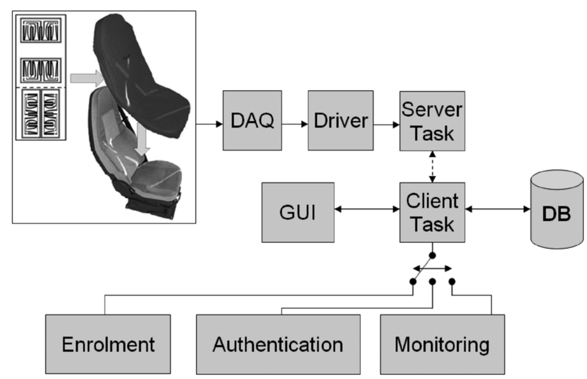

Fig. 7. Server side sensing seat system block schema.

IV. Recording Protocol

The recording protocol was defined as an interactive procedure where the subject cooperates with the system in order to perform the enrollment and authentication tasks [Fig. 6(a), (b)]. The monitoring task is performed in real time by the system and the authentication procedure has to be repeated if the absence of the subject is detected [Fig. 6(c)]. During the enrollment and the authentication steps, the user is asked to sit in turn in two predefined positions. The first position requires the subject to be normally seated and to be in contact with both the bottom and the upper side of the sensing cover. In the second predefined position, the subject leans forward so he is not in contact with the upper side of the sensing cover.

In the case of the enrollment procedure, the new subject is asked to repeat the measurement ten times for each predefined position, while just one measurement for each predefined position is carried out during the authentication procedure. During the repeated measurements, the subject remains seated and is instructed by the system to move only the torso to switch between the two predefined positions. No specific requirement is needed for feet, hand, or arm placement and the subject should stay seated naturally. Each measurement requires a few seconds to ensure the steady state is gained for each strain sensor signal as shown in Fig. 2(b). During data acquisition, a measurement quality level is evaluated on the basis of the steady-state changes of the signals belonging to each strain sensor. The measurement quality increases as the steady-state values become stable. The measurement is valid if the quality level is above a predefined threshold over a 5-s period. Adopting this strategy, each measurement requires at least 5 s, depending on how well the subject cooperates with the system.

V. Software Architecture

Since the sensing seat system is a biometric system, the software architecture was developed as a software library whose public interface follows the protocol supplied by the BioSec API that uses the open source BioAPI layer [11], [12]. Such an interface ensures data security and ethical issues to be addressed and makes the system able to be easily employed in different application scenarios.

Internally, a server task runs and performs the data acquisition through a driver layer that communicates with the DAQ. The server task asynchronously sends notification messages to the client task that runs when the enrollment, authentication, or monitoring procedures are active (i.e., the capture process is requested by the client side, Fig. 7). For each user enrolled in the system, a personal classifier is built and trained on the basis of data stored during the enrollment stage. Since each classifier is designed to discriminate whether the claiming subject is an impostor or not, biometric rates versus the decision threshold are subsequently calculated: false acceptance rate (FAR), true acceptance rate (TAR), false rejection rate (FRR), and true rejection rate (TRR). On the basis of the intersection of the FAR and FRR curves, the equal error rate (EER) is evaluated and an optimal threshold is obtained for each classifier.

From the client side, the sensing seat system transparently appears as a biometric authenticated sensor able to perform data capture during the enrollment and authentication procedures. During the data capture process, an internal graphical user interface implements the recording protocol and interacts with the human subject. The result of the capture process includes the claiming subject identifier, the measurement date time, the measurement quality level, and the array of the steady-state value of the signals acquired from each strain sensor. The sensing seat modality provides the templates matching functionality on the basis of data previously stored during the enrollment stage and data belonging to the actual authentication stage, supplying a biometric score containing the results of the internal classification modules.

As an enrollment or authentication session is successfully completed, the training step is repeated in order to take into account the new extracted signatures. In particular, since for each subject only the ten most recent measurements are loaded from the database, the described procedure guarantees the adaptation of the system on the short-time small changes in the physical structure of each subject.

During the monitoring task, the processing system runs continuously in parallel with the acquisition system. Since the *nobody* user is an enrolled user as well as the other real users, the system is able to detect his presence (i.e., nobody is seated on the sensing seat). Starting from this information, the system is able to detect if the user must repeat the authentication procedure. Due to the mechanical and chemical properties of the adopted sensor technology, the voltage states covered during the strain and the subsequent release of the sensor are not the same. Since this hysteresis effect does not interfere with the steady-state value, the system is able to detect the presence of an impostor that tries to sit down just after a few seconds a granted user left the sensing seat.

VI. Classification Modules

The preliminary prototype of the sensing seat system was tested using different classification modules over the same data: minimum distance classifer (MDC), support vector machine (SVM), principal component analysis (PCA) [13], probabilistic neural networks (PNNs), multilayer perceptron (MLP) [14], and Kohonen self-organizing map (KSOM). Except for MDC, all the other modules showed a high degree of classification capability. Since the authentication system is designed to be finally implemented using a low-cost microcontroller where the computational efficiency (in terms of memory space and computing time) has to be taken into account, the authors decided to employ the MLP and KSOM classifiers within the final prototype. Indeed, while SVM, PCA, and PNN require enough memory space to internally store the reference data (i.e., the training set), the MLP and the KSOM show a higher training computing time but, on the other hand, they need a low memory space to save their trained status (synaptic weights) and a very low computing time to perform a test step (useful in real-time application and especially during the monitoring task execution). Due to the above-mentioned reasons, a KSOM and an MLP were employed for each of the two predefined positions and for each user enrolled into the system. That is, each subject is associated with four classification modules.

Each module receives the input vector from the capture process. The input vector is an array of voltage information whose elements are the normalized output of the sensing seat system (each element is a floating point value representing the differential of voltage potential measured at the ends of each strain sensor). Each classifier receives the filtered input data (low-pass filter with a cut frequency equal to 10 Hz). The sensing seat system is equipped with 28 strain sensors, and the input vector is denoted as $X = (x_1, x_2, \ldots, x_N)$ with $N = 28$.

Each personal classification module belonging to a particular human subject is trained to detect whether the claiming subject is an impostor or not. That is, each module performs the classification task over two classes: the subject is who he claims to be; the subject is an impostor.

A. Kohonen Self-Organizing Map (KSOM)

A KSOM [15], [16] maps the original space into a two-dimensional net of neurons in such a way that close neurons respond to similar signals, in order to solve classification tasks and to find structures in data. KSOMs are unsupervised neural networks; i.e., they exploit similarities of samples apart from the class to which they belong. In the unsupervised training process, the synaptic weight vectors of the artificial neurons of the KSOM are adapted by means of the training data set examples in such a way that the KSOM supplies the best possible representation to the training data set. The synaptic weight vector of an artificial neuron of a KSOM corresponds to the feature vector of an object in the feature space under study.

In this work, the integrate-and-fire neuron model was used and the winner-takes-all training strategy was adopted using a distance-based learning method. A decay factor over epoch time was used for both the learning rate and the learning radius. According to the Kohonen map topology, all the elements of the input vector are connected to all the artificial neurons of the KSOM.

For each input vector $X = (x_1, x_2, \ldots, x_N)$, the squared distance $D_j^2 = \sum_{i=1}^{N}(x_i - w_{j,i})$ of each jth unit from the input vector is calculated. The unit z belonging to the minimum distance (i.e., $D_z^2 = min_j\{D_j^2\}$) is the winning unit. The weights $w_{j,i}$ of the ith synaptic connection of the jth neuron at the example time t and at the epoch time T, is modified as follows:

$$\Delta w_{j,i}(t) = \alpha(T) r_{j,z}(T) \left[x_i - w_{j,i}(t-1)\right]$$

where

1) $\alpha(T) = f_\alpha \alpha(T-1)$ is the learning rate with a decay factor f_α;
2) $r_{j,z}(T) = e^{-(d_{j,z}^2/\sigma(T)^2)}$ is the feedback function of the neuron j to the winning neuron z;
3) $d_{j,z}$ is the Euclidean distance between the jth and the zth units within the two-dimensional Kohonen map;

4) $\sigma(T) = f_\sigma \sigma(T-1)$ is learning radius with a decay factor f_σ.

After the training process, a supervised labeling step is performed. Cluster labels are assigned to the individual artificial neurons. This is done via the interpretation of the content of the synaptic weight vectors (feature vectors) of the artificial neurons. Here the same label can be assigned to several artificial neurons so that each cluster can be represented by several artificial neurons. After validation of the KSOM from examples of a test data set, performance of the classification task is commonly evaluated using the above-mentioned confusion matrix. In order to check the generalization capability of the neural network, a cross-validation process is carried out.

In this work, a KSOM with 8 $\times$ 8 units was adopted, the parameters were set to $\alpha(0) = 0.9$, $f_\alpha = 0.85$, $\sigma(0) = max_{j,i}\{d_{j,i}\}$, $f_\sigma = 0.9$, and a training step of 5000 epochs was performed.

B. Multilayer Perceptron (MLP)

The MLP [17] is an artificial neural network, allowing representation of the relationships between input and output values. This type of network is trained with the help of a supervised learning method, i.e., input and output values are specified and the relationships between them learned. The neural network approximates every nonlinear mapping of the form $y = f(x)$. Every data record consists of input data and the corresponding output data. The MLP learns the input–output behavior of the system examined via a training data set. In the training phase, for each data record, each activation function of the artificial neurons is calculated.

In this work, the integrate-and-fire neuron model was used and the back-propagation training strategy was adopted using the delta-rule learning method. A decay factor over epoch time was used for both the learning rate and the momentum. According to the MLP topology, each element of the input vector is connected to a correspondent unit within the input layer. One hidden layer was employed, where each unit is connected to each unit in the input layer and to a bias unit. Each unit of the output layer is connected to each unit of the hidden layer and to the bias unit.

The weight $w_{j,i}$ of a generic neuron i at the example time t and at the epoch time T, according to the input vector $X = (x_1, x_2, \ldots, x_N)$ is modified on the basis of a well-established technique, the propagation of the resulting error between the input and the output values. The MLP is able to train itself by propagating the resulting error δ backward following the back-propagation algorithm. δ is calculated as follows:

$$\delta_j = \begin{cases} f'(I_j)(z_j - o_j) | j \in \text{output layer} \\ f'(I_j) \sum_i (\delta_i w_{j,i}) | j \in \text{hidden layer} \end{cases}$$

and adaptation of the weights results in

$$\Delta w_{j,i}(t) = \alpha(T)\delta_i x_i + \gamma(T)\Delta w_{j,i}(t-1)$$

where

1) z_i is the target value for the ith unit of the output layer;
2) o_i is the output value of the ith unit of the output layer;
3) I_j is the weighted sum of all signals which are active at the input connections of the jth unit;
4) f' is the derivative of the activation sigmoid function f used to compute the output of the unit;
5) $w_{j,i}$ is the weight of the connection between the jth unit (post-synaptic neuron) and and the ith unit (pre-synaptic neuron);
6) $\alpha(T) = f_\alpha \alpha(T-1)$ is the learning rate with a decay factor f_α;
7) $\gamma(T) = f_\gamma \gamma(T-1)$ is the momentum with a decay factor f_γ;
8) x_i is the input data at the concerned connection.

The response of the MLP is a boolean vector; each element represents the activation function of an output neuron. After the training process, the performance of the classification task is commonly evaluated using the confusion matrix. The generic element r_{ij} of the confusion matrix indicates how many times as a percentage a pattern belonging to the class i was classified as belonging to the class j. A more diagonal confusion matrix corresponds to a higher degree of classification. Since each pattern may be confused with more than one pattern, the sum of each row and column may differ from the value of 100%. In order to check the generalization capability of the neural network, a cross-validation process is carried out.

In this work, 28 units were used in the input layer, 10 units in the hidden layer and 1 unit in the output layer. The parameters were set to $\alpha(0) = 0.9$, $f_\alpha = 0.85$, $\gamma(0) = 0.9$, $f_\gamma = 0.9$, and a training step of 5000 epochs was performed.

C. Biometric Rates

For each measurement, the 28-components steady-state voltage vector is sent to the classification modules (one KSOM and one MLP) corresponding to the specific predefined position. As the enrollment task is completed and the training step is performed, the KSOM will show two regions belonging to the two output classes (impostor, not an impostor). During the authentication task, the KSOM response is supplied by the region the winning unit belongs to. The MLP response is supplied by the output unit according to its activation level.

After the training phase, the classification level and a threshold level were taken into account for each classification module according to the following criteria.

1) KSOM: The winning neuron has the minimum Euclidean distance between its synaptic weights and the input data; a low distance value corresponds to a high classification level, while a high distance value corresponds to a low classification level; if the distance value of the winning neuron is higher than the threshold level, the system rejects the subject even if he is not classified as an impostor by the KSOM.
2) MLP: A low activation value of the output unit corresponds to a low classification level, while a high activation value corresponds to a high classification level; if the activation value of the winning neuron is below the threshold level, the system rejects the subject.

Biometric rate (FAR, FRR, TAR, and TRR) curves versus the threshold level are computed with the aim to find the EER for each classification module. The threshold level corresponding

TABLE II
ACCEPTANCE AND REJECTION RATES USING THE PERSONAL CLASSIFICATION MODULES AFTER THE TEST PHASE. VALUES ARE AVERAGED OVER THE CLASSIFICATION MODULES BELONGING TO ALL THE ENROLLED SUBJECTS. EACH CLASSIFICATION MODULE USED THE INTERNALLY STORED OPTIMAL THRESHOLD LEVEL THAT CORRESPONDS TO THE EER FOUND DURING THE TRAINING PHASE

	TAR	**FAR**	**TRR**	**FRR**	**EER**
KSOM (1^{st} **position**)	90.4%	5.4%	94.6%	9.6%	2.8%
MLP (1^{st} **position**)	93.2%	4.3%	95.7%	6.8%	2.2%
KSOM (2^{nd} **position**)	93.2%	4.0%	96.0%	6.8%	2.0%
MLP (2^{nd} **position**)	94.3%	3.0%	97.0%	5.7%	1.7%

to the EER is then used, within the test phase, as the optimal threshold for the classifier.

VII. MEASUREMENT CAMPAIGN AND RESULTS

Tests were conducted on 40 human subjects (10 repeated measures with 2 predefined positions) using 20 couples (10 men and 10 women ranging from 20 to 40 years old) of physically similar subjects (weight ranging from 60 to 90 kg and height ranging from 160 to 180 cm), obtaining a total of 800 samples evenly distributed among postures. The measurements were carried during a time period of 20 days, performing one session every two days. During each session, four subjects were taken into account. Each subject used different clothes at each session. For each enrolled subject, the personal classifiers were trained on the basis of half of the data belonging to the subject and to half of the impostors. All the combinations were performed using a leaving-half-out cross-validation strategy. After the evaluation of the biometric rates, the optimal threshold was found for each classification module and the test step was performed over the remaining half data. Test results are reported in Table II.

The correct recognition percentage (TAR) assesses on 93% $+/-$ 2% (an enrolled subject claims to be himself, FRR $=$ $7\% + / - 2\%$), while the correct rejection percentage (TRR) assesses on 96% $+/-$ 2% (an unenrolled subject claims to be an enrolled subject, FAR $= 4\% + / - 2\%$). The continuous monitoring was also tested. The system is currently able to recognize the absence of the human subject in less than 1 s with a 100% success (more than 100 measurements were carried out).

Besides the security role, the reported FRRs seem too high to ensure a convenience factor within automotive applications. However, according to the HUMABIO project concept, a multibiometric strategy should be employed to decrease the final FRR and to use the sensing seat system in real scenarios addressing both use convenience and security issues. Indeed, multibiometric systems demonstrate the noteworthy advantages over their unimodal counterparts [18], [19]. Multimodal tests were conducted in a truck simulator at VOLVO using three cooperative authentication systems: sensing seat system, face recognition system, and voice recognition system. During the multimodal tests, 20 users were enrolled and the authentication procedure was carried out taking into account enrolled subjects and impostors. As a result, while the single modalities showed high FRR values (7%, 2%, 1.5%, respectively), the multimodal fusion based on SVM showed a final FRR of 1% $+/-$ 0.5%.

VIII. PERFORMANCE FACTORS

The classification algorithms of the sensing seat system are based on the analysis of the steady-state value of the signals acquired from the strain sensors of the sensing cover. During the enrollment and the authentication tasks, the human subject is asked to cooperate with the system through an interactive procedure. As a result, each factor that affects the stability of the signals acquired from the strain sensors may decrease the performance of the system.

A list of restrictions, parameters, and factors that affect the performance of the sensing seat recognition module are reported below.

1) Specific restrictions and parameters (environmental and other) that affect the performance of the sensing seat recognition module are as follows.
   a) Environmental temperature:
      i) Temperature variation: the resistance temperature coefficient (RTC) of the Elastosil LR 3162 A/B is equal to 0.08 $\Omega \cdot {}^{\circ}\mathrm{K}^{-1}$, resulting in a very small resistance variation due to temperature effects compared to the variations induced by the strain sensor stretching ($1\ \mathrm{k}\Omega \cdot \mathrm{cm}^{-1}$);
      ii) Temperature range: according to WACKER Ltd specifications [20], the electrical properties of the Elastosil LR 3162 A/B product are almost completely independent from temperature in the range from $-50\ {}^{\circ}\mathrm{C}$ to $+200\ {}^{\circ}\mathrm{C}$.
   b) Movements and vibrations [21] may cause the steady-state value of the strain sensor signals to be not stable. This may subsequently cause a decrease of the performance of the classification algorithms.
      i) The subject is moving while the signals are captured from the sensing cover system;
      ii) Environmental vibrations (e.g., the truck or car engine is running) may cause movements of the subject even if the subject cooperates to stay still.
   c) Changes of the human profile:
      i) presence of wallet and/or coat;
      ii) changes in the way the same human subject sits in each predefined position;
      iii) changes in the human subject's profile (aging, changes in weight).
2) List of factors that may cause system failures:
   a) malfunctioning of the power supply module;
   b) malfunctioning of the front-end hardware module;
   c) malfunctioning of the DAQ.

The sensing seat system is not equipped with a temperature sensor, so the system will not be able to automatically compensate for temperature variations. However, as it is shown in 1(a)i, these effects are negligible within the operating range described in 1(a)ii.

Points 1(b)i and 1(b)ii will be monitored using the quality of measurement property provided by the capture process. This property is an index of the signal stability over time during the capture process. Point 1(c)i should be addressed by the user interface, asking the subject to remove wallets and coat and to empty his/her pockets before performing the enrollment and authentication processes. Points 1(c)ii and 1(c)ii will result in the human subject signature to be not so "far" from the signature information stored into the database. However, the time-stamp information for each measurement in the signature is taken into account for these kinds of situations. It is supposed that the changes (the way of sitting, the weight, the aging) will be minor especially if they are considered over a short period of time. Once the user is enrolled, the time-stamp is saved into the signature for each measurement (related to several repeated measurement for each predefined position). If the user continuously performs the authentication task in the sensing seat system (let us say, once a month at least) and if he/she will be correctly authenticated, the new measurements (probably a bit different from the previous measurements) should be saved in the database and the classifiers should be trained again taking into account a last-in-first-out (LIFO) queue of measurements. Points 2a, 2b, and 2c may be taken into account performing a test of a baseline measurement (i.e., matching the signature acquired while nobody is seated on the sensing seat).

IX. Conclusion

In this paper, the development of a novel sensing seat system based on an unobtrusive piezoresistive sensor array was described. The main result is a positive assessment of the use of the reported sensing seat in the authentication task, showing the robustness of the system in terms of biometric rates. Another relevant result is the assessment of the strain sensor technology and of the classification modules based on artificial neural network personal classifiers. The modular software library compliant with BioAPI makes the sensing seat system able to act in different scenarios and to be employed together and in cooperation with other authentication systems.

The proposed system is still under development even if the actual prototype was successfully tested within unimodal and multimodal environments. Actually the system needs the cooperation of the subject in order to work properly and other open issues include the performance study in extreme environmental conditions (e.g., very low and very high environmental temperature scenarios). Moreover, the strain sensor stability over time as well as its chemical properties must be investigated thoroughly in order to study the sensor degeneration over time (i.e., sensor aging). Additionally, in order to make the system really unobtrusive, the objects inside the clothes and the pockets (e.g., keys, wallet) should be treated as a point of disturbance to increase the final user convenience. Even the sensing seat system is now focused on the analysis of static data (i.e., steady-state values of the signals), the study of the dynamics of the signals should be investigated to improve the monitoring task performances. All the above mentioned topics will be taken into account in future developments.

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