A Smart Ink Pen for the Ecological Assessment of Age-Related Changes in Writing and Tremor Features

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***Abstract*— We present the development of a novel smart ink pen instrumented with force and motion sensors designed for the quantitative and ecological assessment of daily-life handwriting. This work aims at testing the pen's sensors and algorithms and the use of the smartpen to detect age-related changes in writing and tremor parameters during daily-life handwriting. A comparison against reference instruments was carried out to validate the pen tip force during static and dynamic conditions, the pen's tilt angle, and the algorithm for the segmentation of the force signal into strokes. The smartpen was tested on 43 healthy adults divided into three age groups (young, middle-old, and old) during unconstrained handwriting on paper. The validation of the pen's sensors and algorithms reported excellent results. A solid test–retest reliability was found in the writing and tremor indicators extracted from both young and old adults. As for the age-related analysis, the older age groups were characterized by an increase of temporal writing measures, a more uniform writing pressure, and more repetitive and predictable tremor oscillation components. The greatest accomplishment of our smart ink pen is the ability to combine the advantages of the digitizing tablet technology with the natural "feel," the ease of use, and the ecological validity of the traditional pen-and-paper approach. The proposed solution represents an important step toward a simple, ecologically valid, reliable quantitative assessment of daily-life handwriting. Our smartpen is particularly suitable for daily-life telemonitoring applications in a number of important health-related fields.**

***Index Terms*— Aging, handwriting, Internet of Things (IoT), smart ink pen, smart objects, tremor.**

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I. Introduction

HANDWRITING is a continuous cognitive-motor task acquired during development that requires high skill and cerebral activation [1]. Handwriting is a familiar and straightforward activity for almost all literate adults, which was proven to be a very useful biomarker. Indeed, the motor performance required for writing depends upon the coordinated function by the brain, in combination with the neuromuscular and visual systems. This deteriorates to some extent in all older adults and even more so when the neurological disease is present [2].

For this reason, the analysis of this everyday activity has been leveraged for assessing different conditions. As for neurology, kinematic analysis of handwriting has been used as a clinical tool highly sensitive to even subtle dysfunctions, particularly useful in Parkinson's disease (PD) [2], Dystonia [3], and Huntington's disease [4] evaluation. Given its fine motor nature, handwriting analysis turned out to be a very useful tool also for the investigation of tremor [5]. In addition, the handwriting was studied to discriminate different levels of severity in terms of age-related cognitive decline [6]. Against this background, the characterization of age-related changes in handwriting is key since it may allow distinguishing physiological variation simply due to age, from abnormal changes, possibly related to neurological conditions or cognitive decline.

Early work used ink pen and paper notebook to register the subject's writing outcome [2]. On the one hand, this approach can be considered worthwhile in the clinical environment, due to its simplicity, since it does not require the support of a technician. On the other hand, the assessment of the paper-and-pen technique requires the expertise of a clinical professional to evaluate the writing outcome without the support of any quantitative data: such an approach does not match the current needs of the health systems that count on the achievements of telemedicine to solve problems, such as the limited availability of specialists, the reduced time to conduct such tests, and the difficulty for some patients—especially the older ones—to reach the examination site [7]. For this reason, in most of the recent studies, the paper-and-pen approach was replaced by digitizers and tablets able to return the 2-D trajectory of the writing trace [6], [8], [9]. The digitalization of data allows extracting quantitative parameters to objectively assess handwriting and achieving remote monitoring of the user's performance. However, such an approach is questioned since it constraints the user to write on a relatively small surface (typically the one of a tablet) that is not the standard writing surface; in this way, the naturalness of the gesture is undermined [10]. As a consequence, this approach lacks ecological validity since the experimental context does not match the real-world phenomenon [11]. Moreover, the use of such technology may not be so straightforward particularly when dealing with elder users, thus requiring the technical support of an operator.

To combine the ecological validity of the first approach and the quantitative assessment achieved by current technologies, we designed a novel smart ink pen that allows users to write on a common piece of paper while acquiring motion and force data. Indeed, the ink pen is instrumented with a force sensor, to measure the normal force applied on the pen tip while writing, and inertial sensors, to collect motion and tremor information during writing task execution. To increase usability, the pen was designed to autonomously record data when used. To foster telemonitoring, an *ad hoc* software was created to automatically download the writing data and compute relevant handwriting and tremor indicators. Another element of the newness of our approach is the ecological validity and the transparency of the protocol. Indeed, different from the vast majority of studies [6], [8], [9], in which handwriting is studied under controlled conditions (with the subject copying or writing previously defined text), we decided to propose tasks mimicking daily-life writing without constraining the writing modality or content.

This article is organized as follows. Section II presents the design and development process, the validation of sensors, algorithms, and indicators and the study of age-related changes in handwriting and tremor parameters extracted during a daily-life writing task. Results are reported in Section III and discussed in Section IV. Section V draws the conclusions of the work. A preliminary version of this work has been reported [12], [13].

II. Materials and Methods

A. Pen

To realize a smart writing object that resembles a common ink pen, a careful design of the microarchitecture to sense and transmit the data has been carried out. The developed pen has the following dimensions: height: 147 mm, maximum diameter: 14.65 mm, and weight: 48 g (see Fig. 1).

1) Hardware: The pen incorporates the internal electronic components to acquire, store, and send the handwriting data. The electronics are integrated into three printed circuit boards (PCB) located in the upper part of the pen. PCB1 has a dimension of 28.5 × 8 mm^2 and is the core PCB; it includes an ultralow-power Cortex 32bit CPU (STM32L476) to acquire, filter, and transmit the signal, a BlueNRG-MS single-mode network processor (compliant with Bluetooth specification v4.1) to implement Bluetooth Low Energy (BLE) connectivity, and 1-MB flash memory for storage purposes.

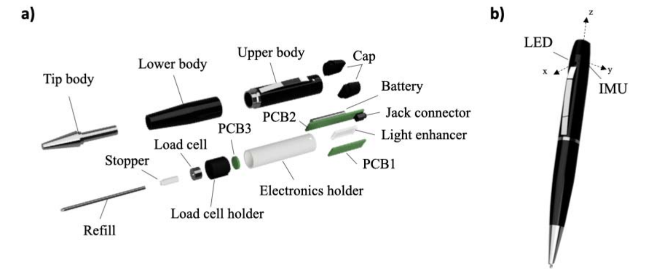

Fig. 1. (a) Rendering image of the smart ink pen and its internal components. (b) External view of the smart ink pen.

In terms of sensors, inertial signals are acquired through 3-D linear accelerometers and gyroscopes (LSM6DSM iNEMO 6DoF), while the writing force exerted on the tip is measured through a miniaturized load cell (FC8E by Forsentek; Ø 1.6 mm; 50-N capacity) mounted with the lower face pressing on the refill stopper. PCB2 includes a rechargeable Li-ion p-i-n-type battery by Panasonic Corporation, Osaka, Japan, with a coaxial power connector accessible from the pen cap and the battery protection circuit. PCB3, with a rounded shape, is placed in the load cell holder and includes the preamplification circuit for the load cell data. Pen functions in self-operated through movement detection or BLE connection request; therefore, no activation button is available for the end-user. Nonetheless, a LED is visible to indicate the operating mode and the battery state of the pen. All the electronics are protected and securely fixed inside a 3-D printed plastic case.

Fig. 2 shows the signal conditioning circuit for the load cell. The circuit comprises a low-noise instrumentation amplifier (AD623RMZ (IC1) hosted by PCB3), connected to a 16-bit high-quality, low-noise, low-power fully differential ADC (ADS1115I, (IC3) hosted by PCB1), both powered by a 3.3VDC single supply low dropout voltage regulator (LD3985M33R, (IC4) hosted by PCB1). The IC4 receives energy directly from the battery (PCB2), thus reducing the possible interference arising from digital and wireless parts of the mainboard (PCB1).

The instrumentation amplifier (IC1) has a gain set at 101 and a low-noise, low-power Rail-to-Rail Input and Output (RRIO) dual operational amplifiers. The differential input filter has been set to 1.5 kHz, to allow a first stage filtering before the connection wires to the IC1. The output baseline (VREF) has been set to VCC/3 by the IC2A, to allow a fully differential analog to digital conversion without losing the possibility to investigate possible preloading effects of the load cell caused by the mechanic assembly. The output of IC1 and the VREF signals coming from IC2 have been connected to the mainboard (PCB1), respectively, to the positive (AIN1+) and negative (AIN1−) channel inputs and of the ADC (IC3). The ADC samples at 50 Samples/s. The internal pin grid array (PGA) of the ADC has been programed to 2, providing a total gain of 13.3 mV/N. An antialiasing filter has been placed near 0.1 Hz to preserve the signal information. The inductor L1 is a ferrite bead with an impedance of 60 Ω measured at 100 MHz. Multilayer ceramic capacitors were used.

2) Software: The firmware was designed with the aim of maximizing battery duration and usability of the smartpen for

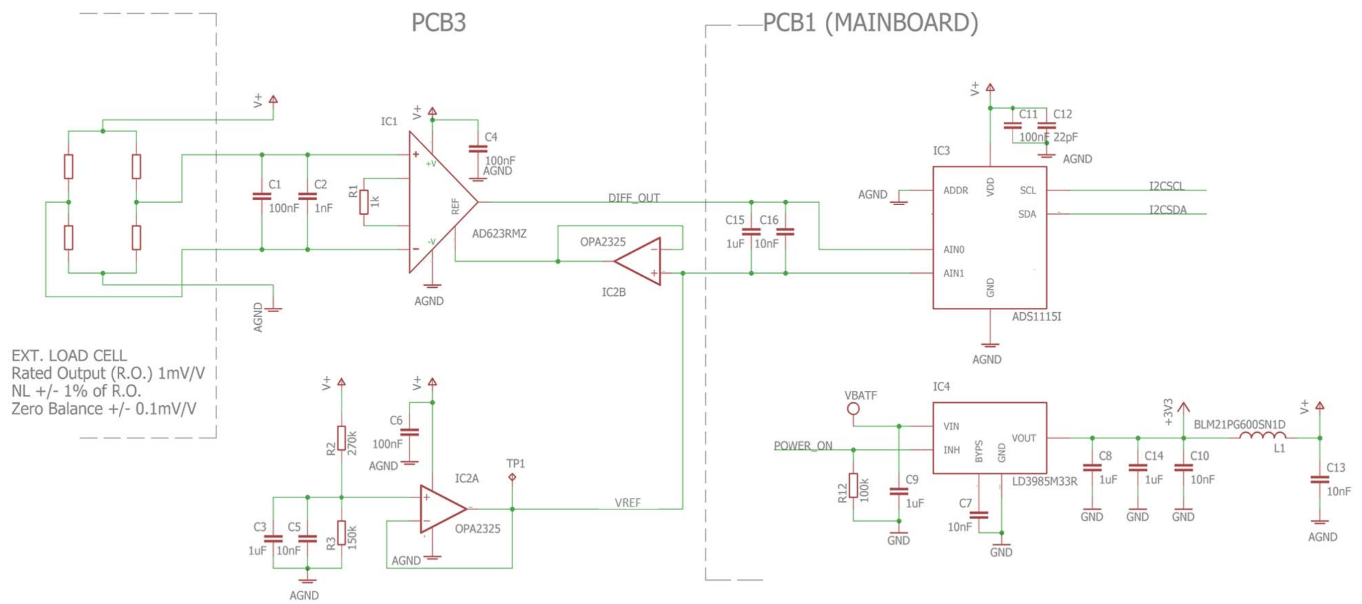

Fig. 2. Conditional circuits of the smartpen.

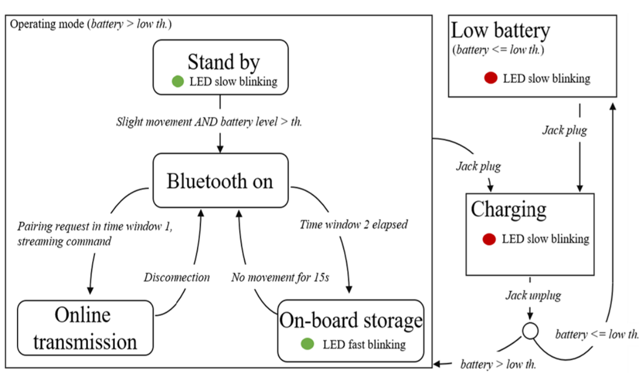

Fig. 3. Block diagram of the firmware operating modes.

not expert users, such as older adults. To extend the possible applications of the pen, two modalities of data transfer are envisaged.

1) *Online Data Transmission:* The microcontroller reads the data from the sensors and transmits them in real-time through BLE.

2) *Onboard Storage:* When the object is used, sensor data are sampled, saved on the flash memory, and downloaded afterward. The firmware comprises six operating modes, and Fig. 3 shows its block diagram representation. When, in the standby state, the battery is set to saving mode and, just to advise that the pen is available, a green LED blinks at a low frequency. Only when a slight movement of the object is detected by the accelerometer, and the charge level is over a specific threshold (to prevent using the object when the battery is too low), the BLE module of the object is switched ON. In this Bluetooth ON-state, the pen is available for any pairing connection within a certain time window. If a pairing request is received within the time window, followed by a start streaming command, the online transmission state is enabled, and the object transmits the information packages at a frequency of 50 Hz. The object returns to the Bluetooth ON-state once a disconnection request is received. Otherwise, if (in the Bluetooth ON-state) a pairing connection is not received within the time window and the object is moved by the user, the transition to the onboard storage state is triggered. At this point, the object starts storing data packages onboard at 50 Hz and stops when left stationery for 15 s, thus triggering a transaction to the Bluetooth ON-state. When the battery level is below a certain threshold, the object goes into the low battery state in which a red LED blinks to notify the user that a charge is needed. Every time the pen is connected to a charger, the state moves to charging, with the red LED blinking at a higher frequency.

The data package, sampled at 50 Hz, includes a timestamp, the three-axis acceleration [m/s^2], the three-axis angular velocity [rad/s], and the writing force signal exerted on the pen tip.

Finally, software was created to automate the data download and processing procedures.

B. Pen Validation

This section includes the apparatus, the protocols, and the analyses aimed at validating the pen sensors and algorithms.

1) Tip Force Static Calibration: This test has the twofold aim of verifying the linearity of the writing force measurements in the range of the force values exerted during handwriting and estimating the optimal calibration parameters for the conversion of the pen tip force signal to Newton (N) units.

The setup shown in Fig. 4(a) was devised to keep the pen in the vertical position and to place the test weights at the top; it includes two 3-D printed arms to hold the device with the minimum friction and a circular flat base to accommodate the weights. From the pen load cell, we acquired the normal component of the force signal, F, applied to the tip while increasing the testing weight from 0 to 50 g, with steps of

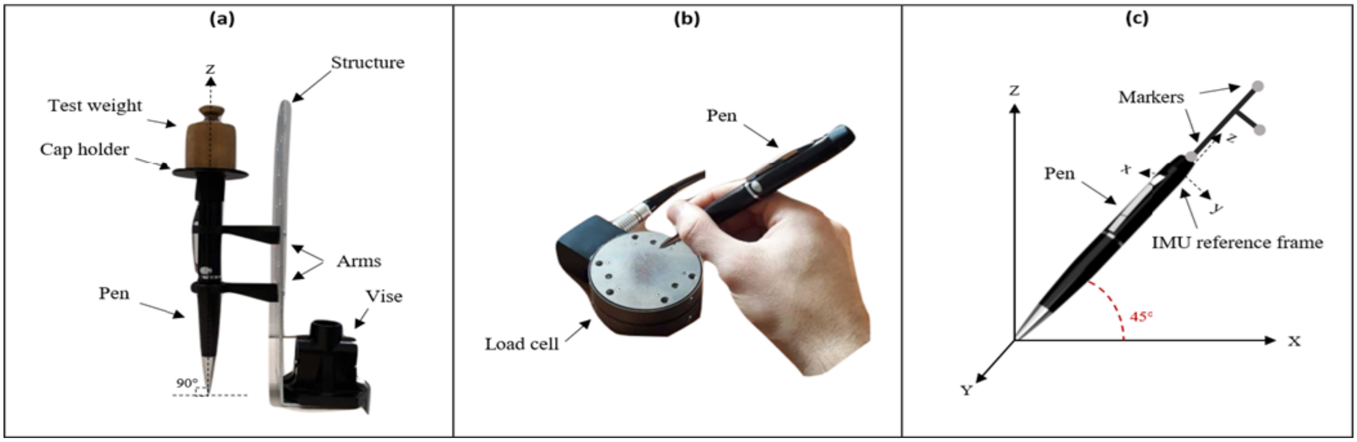

Fig. 4. Experimental setups for pen validation. (a) Static tip force calibration. (b) Dynamic tip force validation. (c) Tilt angle validation.

10 g, and from 50 to 500 g, with steps of 50 g. For each weight increase, the related F measure was obtained as the mean value of the signal over 50 samples after the transient phase.

We computed the linear regression between the measurements of the pen force F and the corresponding testing weights placed on the top of the pen; the selected loss function was the mean squared error (MSE) [14].

2) Tip Force Dynamic Calibration: We validated the writing force signal in dynamic conditions (i.e., during the handwriting activity), comparing the pen force signal F with an external force reference signal F_{ext}, obtained through the M01–500N Golden Type (by Sunrise Instruments, Canton, MI, USA) load cell sensor. The protocol consisted of a 2-min free writing test performed by a healthy adult, who used the smartpen to write over the load cell surface [see Fig. 4(b)]. The two signals were synchronized using the peak of cross correlation. We evaluated Pearson's correlation coefficient ρ_d between F and F_{ext} during the writing task.

3) Tilt Angle Validation: We compared the tilt angle θ_{pen} obtained from the pen's motion sensors with a reference tilt angle θ_{ext} obtained from the optoelectronic motion capture system SMART DX 400 (BTS SPA, IT). To this aim, a 3-D-printed tool with three retroreflective markers was built and positioned on the top of the pen to record the orientation of the pen body [see Fig. 4(c)]. The acquisition protocol included two different trials performed by a healthy adult: in the first one, the subject was requested to draw six straight lines on a sheet of paper, three with the smartpen tilt kept approximately at 45°, and three at 70°. In the second trial, the subject was asked to write freely for three minutes, and no constraint on the pen tilt was imposed.

In quasi-static conditions (i.e., when the pen is moved very slowly), we computed the tilt angle, θ_{pen}, using the approximation in

$$\vartheta_{\text{acc}} = \sin^{-1}\left(\frac{a_z}{g}\right) \tag{1}$$

where a_z is the z-axis acceleration signal and $g = 9.81$ m/s is the gravitational acceleration; for small tilt angles ($\vartheta \ll 1°$), we linearized the relation as in

$$\vartheta_{\text{acc}} \approx \frac{a_z}{g}. \tag{2}$$

The estimate tilt angle pen, θ_{pen}, corresponds to the approximation, θ_{acc}, for slow movements.

In nonstationary conditions, instead, we considered a low-pass filtered (cut off 10 Hz) a_z in the computation of θ_{acc} to get rid of the z-axis acceleration components not related to the gravity load. Indeed, at high frequencies, the variation of the tilt angle is coupled with nonnegligible accelerations that lead to consistent errors in the estimation of the tilt angle from the accelerometers [15]. Furthermore, to avoid the estimate to diverge, we combined the estimate from the accelerometer signal of the tilt angle with its rate estimate from the gyroscopes signals, $\dot{\vartheta}_{\text{gyr}}$, obtained by integrating (in the time domain) the angular velocity in the x- and y-axes. We used the sensor fusion filter in (4) [15] to obtain the estimate of the tilt angle rate $\dot{\vartheta}_{\text{gyr}}$

$$\dot{\vartheta}_{\text{pen}} = k_1\dot{\vartheta}_{\text{gyr}} + k_2(\vartheta_{\text{acc}} - \vartheta_{\text{pen}}) \tag{3}$$

where k_1 and k_2 are two constants empirically set to 1.5 and 0.4, respectively, to achieve the minimum discrepancy between the estimate and the measured tilt angle.

Finally, we compared the two tilt angle signals by calculating Pearson's correlation coefficient ρ_t and the root-mean-squared error (RMSE) between $\theta_{\text{pen}}$and θ_{ext}, during the writing tasks.

4) Segmentation Into Strokes: The algorithm for the segmentation of the signals into strokes is the preliminary step for the calculation of the handwriting indicators; we define stroke as an interval in which the pen writing force is nonzero. For its validation, we compared the segmentation into strokes computed from the pen force signal, F, with the one extracted from the external load cell reference signal. The signals were acquired using the experimental setup described in Section II-B2 [see Fig. 4(b)] and repeated ten times with different smartpen prototypes. We decided to use ten different pen prototypes to validate the robustness of the segmentation algorithm considering possible differences due to device construction and assembly variabilities. The data acquired with the first three pen prototypes were employed to calibrate the algorithm, while the rest of the data from seven pens was used to evaluate the stroke segmentation algorithm.

For the segmentation into strokes, given the pen force signals F, as a first step, we removed the bias from the force signal; this is particularly important because the force bias may differ between diverse prototypes due to various factors (e.g., the tolerances of the 3-D printed components, the ink refill replacement by the user, and the curvature of the load cell wire during assembly). Since signal processing is fully automated during unsupervised pen usage, we opted for an automatic baseline removal. To do so, we first subtracted from the signal a value corresponding to the mode of the median filter computed over a 50-sample time window. After that, we ran a baseline estimation and denoising using sparsity (BEADS) [16]. Finally, we cropped to 0 all values below an experimentally fixed threshold; this zero-cropping threshold was chosen to optimize the agreement between the stroke identification obtained from the pen (first three pen prototypes) and the reference force signal.

As for the stroke segmentation of the reference force signal, we considered the mean value of a manually selected nonwriting tract as baseline; after baseline removal, we defined the stroke segments as the nonzero parts in the signals.

We detected a total number of 452 strokes in the pen signals. Through a Bland–Altman plot analysis [17], we evaluated the agreement between the stroke durations obtained from the smartpen (last seven prototypes) and from the external force signal. We also computed the linear regression between the stroke durations obtained in the two cases.

C. Handwriting Task

This section includes the protocol and the analysis aimed at studying age-related changes in handwriting and tremor parameters.

1) Protocol: After validation, the smartpen was used to collect handwriting data on a population of healthy young and older adults, with the aim of testing the reliability of the writing and tremor indicators, and to study possible age-related differences in handwriting and tremor features.

The study included voluntary subjects from different age ranges: young adults (age $<$ 50 years) and older adults (age $\geq$ 60 years). The exclusion criterion was any diagnosis of neurological, vascular, or musculoskeletal disorder affecting the upper limbs.

To maximize the ecological validity of the protocol, we decided to propose a task mimicking daily-life writing, without constraining the writing modality or content. Participants were seated at a table and asked to use the instrumented pen with their dominant hand to write seven lines of free text on a paper sheet [5]. Participants executed the task twice, with a between-trial break of at least 4 h. To obtain an ecologically valid test–retest reliability, no constraints on the writing content or modality were imposed on the user.

The Ethical Committee of the Politecnico di Milano, Milan, Italy, approved the study protocol (n. 10/2018).

2) Indicator Extraction: Data analysis was carried out with MATLAB R2018b (Mathworks, Natick, MA, USA).

Starting from the stored data package defined in Section II-A2, a set of writing and tremor indicators are extracted for each subject.

For the writing indicators, as the first thing, we computed the pen tilt over the entire writing period, following the method presented in Section II-B3. The pen tilt during the writing gesture has been included in studies investigating handwriting in a number of conditions [18]–[20]. For this reason, we computed and retained the mean (Tilt_mean) of the pen tilt signal, not including the segments longer than 2 s, which were considered pauses. To evaluate how pen tilt varied during the writing gesture, we also computed and retained the coefficient of variation (Tilt_CV).

After that, the signals were divided into strokes (see Section II-B4). We defined the stroke segments as on-sheet and the complementary nonwriting segments as in-air, not including the segments longer than 2 s, which were considered pauses. After that, since previous work reported irregular writing rhythm with age [21], the following handwriting temporal indicators were computed.

In-Air Time, $t_{air}[s]$: The average duration of the nonwriting segments, averaged over all in-air tracts during the writing task execution.

On-Sheet Time, $t_{sheet}[s]$: The average duration of the on-sheet segments, averaged over all strokes during the writing task execution.

In-Air/On-Sheet Ratio, $t_{a/s}$: The ratio between t_{air} and t_{sheet}.

The force signal of every single stroke was low-pass filtered at 4 Hz (fourth-order Butterworth filter) [22], and the following force-related indicators were computed:

Mean Writing Force, $\bar{F}[N]$: The mean normal force applied to the pen tip in each stroke, averaged over all strokes.

Number of Changes in Force, NCF: The number of local minima and maxima in pen force signal F in a stroke, averaged over all strokes [22].

As for the acceleration signals, a three-axial gravity compensation was carried out for every single stroke. A compensation factor was computed, for each axis separately, as the average of the low-pass filtered single-axis acceleration signal (fourth-order Butterworth cutoff: 3.5 Hz) and then subtracted from the signal itself [23]. After gravity compensation, the signals were low-passed filtered at 4 Hz (fourth-order Butterworth filter), and the 3-D acceleration signal was computed for all the strokes. As a measure of smoothness, which was previously shown to decrease with age [2], we then calculated the Number of Changes in Acceleration (NCA): the number of local minima and maxima in the 3-D acceleration in a stroke, averaged over all strokes.

To study tremor, we used the acceleration signals without distinguishing between on-sheet and in-air tracts. The acceleration signals were cut into 500-sample segments [24]. The acceleration data over the three axes were first band-pass filtered at 0.5–24 Hz (fourth-order Butterworth filter) [25]. The 3-D acceleration signal was then computed. For each segment, the tremor was estimated using the Hilbert–Huang transform (HHT), which consists of the empirical mode decomposition (EMD), followed by the Hilbert spectral analysis [26]. The EMD-based filters' decomposition is based on the local timescale characteristics of the data since EMD does not have any general analytical formulation, unlike other conventional fixed cutoff filtering techniques. For this reason, it was proven to be particularly suitable to study tremors in presence of voluntary motion [27], and it was, thus, preferred to the standard Fourier transform to study tremor frequency components during our handwriting protocol. Once the HHT was applied to the 3-D acceleration segments to estimate tremor, the following indicators were extracted for all the signal segments and then averaged over all segments.

Modal Frequency, f_{mod} [Hz]: The tremor characteristic frequency value that corresponds to the highest peak in the tremor signal power spectrum [28] and has been shown to change in the case of pathology [29].

Approximate Entropy, ApEn: The estimate of the entropy, a regularity statistic measure that quantifies the unpredictability of the fluctuations in a time series signal and returns a value between 0 (high degree of short- and long-term predictabilities) and approximately 2 (completely random signal such as pure white Gaussian noise). For the computation of ApEn [30], "m" (the window length) was set to 2, and "r" (the similarity criterion) was set to 0.2∗SD of the signal, as in [25]. The regularity of tremor has been shown to change with age and pathology [31].

After that, the recurrence quantification analysis (RQA) was applied to the tremor data; it is a nonlinear data analysis method that quantifies the number and duration of recurrences of a dynamical system presented by its phase-space trajectory [32]. The 2-D binary map–recurrence plot (RP) is computed for each tremor signal to visualize the recurrence behavior of the phase-space trajectory of dynamical systems. The following settings were adopted [33]: 1) the delay was estimated with the mutual information method algorithm; 2) the embedding dimension was estimated with the false nearest neighbor (FNN) chaotic algorithm [34]; and 3) the critical radius was set to 20% of the maximum distance (Euclidean distance matrix). From these maps, we obtained the following indicators to describe the complexity of tremor [24].

Recurrence Rate,% RR [%]: It expresses the self-similarity of the tremor time series during handwriting.

Determinism,%DET [%]: An index of the degree of %DET, which expresses the predictability of tremor.

The higher these indicators, the lower the tremor complexity [24].

3) Statistical Analysis: Statistics were run using RStudio version 1.2.5033 (RStudio Inc., Boston, MA, USA). The significance level was set at 5% for all tests.

The goals of our statistical analysis were to: 1) check the reliability of the computed indicators in a test–retest design and 2) study possible significant variations of these quantities with age in healthy subjects.

Data acquired in the two sessions were used to evaluate the relative and absolute reliability of the computed indicators, for young and older adults, separately. To do so, for each continuous indicator, we first conducted a Lilliefors test to verify normality and a paired t-test to assess the absence of systematic bias between the measurements in the first and second sessions of the test. We evaluated the reliability by

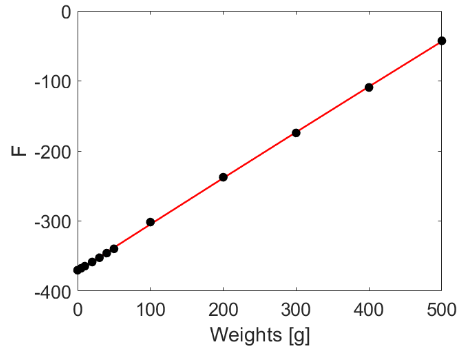

Fig. 5. Linear regression between the test weights (x-axis) and the pen measurements (y-axis).

computing the intraclass correlation coefficients (ICC two-way mixed-effects model, absolute agreement), an index ranging from 0 to 1; ICC values of 0.5, 0.75, and 0.9 indicate moderate, good, and excellent reliabilities, respectively [35]. Absolute reliability was assessed computing the standard error of measurement (SEM), as in

$$\mathrm{SEM} = \mathrm{SD} \times \sqrt{1 - \mathrm{ICC}} \tag{4}$$

where SD is the standard deviation of the indicator in the test–retest. Given the SEM, the measurement error was estimated through the minimal detectable change (MDC) calculated as in

$$\mathrm{MDC} = \mathrm{SEM} \times 1.96 \times \sqrt{2} \tag{5}$$

where 1.96 is the z-score associated with the 95% level of confidence, and the square root of 2 reflects the additional uncertainty introduced by using scores based on measurements made at two time points [36]. On the other hand, for the two count indicators (NCA and NCF), test–retest concordance between the two test repetitions was investigated by computing Kendall's tau [37].

As for the second aim, we opted for nonparametric statistics after verifying, with a Lilliefors test, that not all indicators were normally distributed. For each indicator, we studied possible between-group differences using the Kruskal–Wallis test, followed by the Wilcoxon pairwise comparisons with the Bonferroni correction in case of significance.

III. Results

A. Pen Validation

1) Tip Force Static Calibration: A strongly significant positive linear regression was observed between the test weights, in grams (g), and the pen measurements (nonscaled units) with a R^2 score of 0.99 (see Fig. 5). We found the linear coefficients, m (slope) and b (intercept), for the force signal calibration equal to 0.62 and −369.7 g, respectively.

2) Tip Force Dynamic Validation: The correlation ρ_d between F and F_{ext} was significant and equal to 0.96. Fig. 6(a) shows the pen force signal and the external sensor force signal superimposed acquired in the first 27 s of the writing task. Both signals are normalized with respect to their maximum value to better visualize the comparison. As noticeable, the

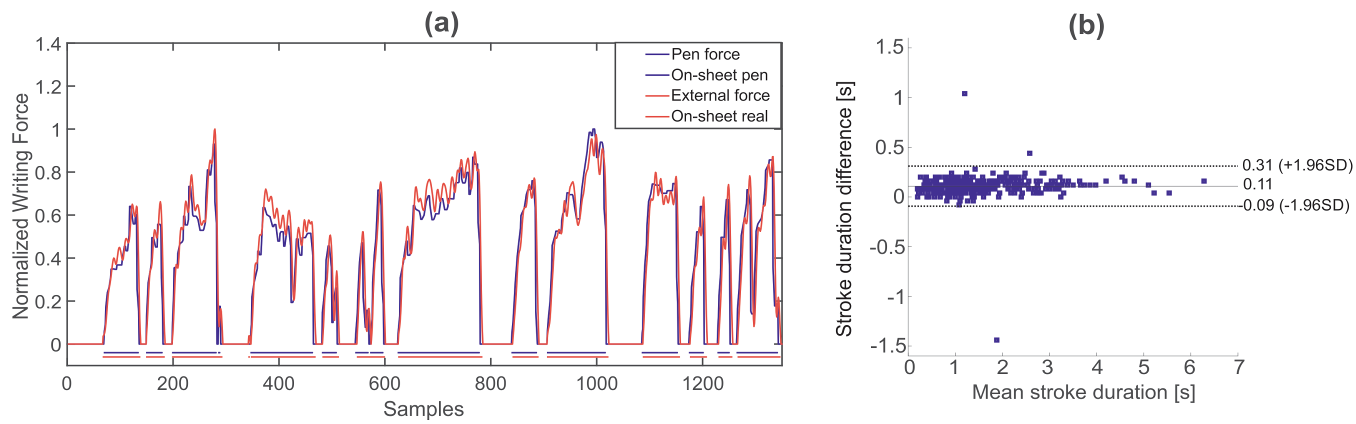

Fig. 6. (a) Aligned and overlapped writing force signals acquired with the pen (blue) and with the external load cell used as reference (red). Below the signals, the colored segments (blue for the pen and red for the external load cell) indicate the detected strokes. (b) Bland–Altman plot with the duration of the strokes detected with the pen and the external load cell signals.

writing force signal F recorded with the pen accurately matched the reference signal F_{ext} from the load cell, with a weak smoothing effect on the fastest components.

3) Tilt Angle Validation: Fig. 7 shows the results of the tilt angle validation. The results in the first writing task reported a significant correlation coefficient ρ_t of 0.89 and an RMSE value of 6.3° between the estimate tilt angle from the pen and the reference angle obtained with the optoelectronic system. In the second task, the correlation was significant with ρ_t equal to 0.78; an RMSE of only 3.8° was reported.

4) Segmentation Into Strokes: Fig. 6(b) shows the Bland–Altman plot for the agreement between the stroke segmentation obtained from the pen writing force signals F and the reference signals from the external sensor F_{ext}; the mean stroke duration (in seconds) is presented in the x-axis, while the difference between the stroke duration between F and F_{ext} is in the y-axis. A total number of 452 strokes were detected, with a mean duration of 0.11 ± 1.96 s. As can be observed from Fig. 6(b), there is an agreement between the stroke duration obtained from the two signals: all data points except three were located inside the confidence interval boundaries of agreement, with no trends in the point distribution.

The linear regression between the stroke duration obtained from F and F_{ext} reported an R^2 score of 0.99. A visual representation of the stroke segmentation in a 27-s-long force signals is shown through horizontal tracts placed below the overlapped time series in Fig. 6(a).

B. Handwriting

A total of 43 subjects was recruited. The young adults group (YY) included 20 subjects [age 28.5 (mean) ± 3.6 (standard deviation) years old; sex: ten male and ten female; and dominant hand: 19 right-handed]; the older adults group included 23 subjects [age 73.4 ± 8.9 years old; sex: eight male and 15 female; and dominant hand: 22 right-handed]. To study how age affects handwriting, the subjects in the older adults group were divided into two based on their age: the subgroup of middle-old adults (EY) included 12 subjects with an age between 60 and 69 years old [age 66.4 ± 2.1

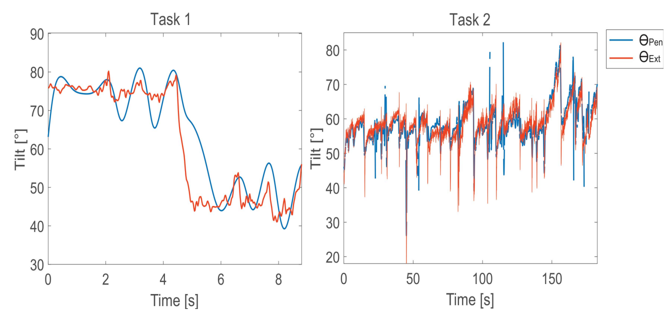

Fig. 7. Tilt angle validation. Each figure shows the aligned and overlapped tilt angle signals computed from the pen sensors (blue) and from the external reference system (red), for both tasks.

years old; sex: six male and six female; and dominant hand: 12 right-handed]; the second subgroup (EE) was composed by 11 old adults with an age above 70-year old [age 81 ± 6.9 years old; sex: two male and nine female; and dominant hand: 10 right-handed]. The choice of separating subgroups in the population over 60 enables a more accurate portrayal of significant life changes. The 70-year old threshold was based on published studies showing that the relationship between age and handwriting movements is likely to be nonlinear with the greatest decline in age-related motor function occurring after the age of 70 [19], [20].

1) Reliability: Table I presents the reliability results for both young and old adults. The test–retest reliability results on the older adult group were computed from the data of 11 subjects who performed the protocol twice. As shown in Table I, excellent or good reliability emerged for all the indicators, for both young and older adults, except for fmod for the old adults, which showed moderate reliability (ICC = 0.68).

2) Age-Related Changes in Handwriting and Tremor: Table II reports the results of the nonparametric statistical analysis that we carried out to test the age effect on the handwriting indicators. Significant between-group differences were found for in-air time (t_{air}), in-air/on-sheet ratio ($t_{a/s}$), NCF, ($ApEn$), %RR, and %DET. Pairwise comparisons highlighted significant changes for: the couples YY–EY and YY–EE for t_{air}

TABLE I

RELIABILITY OF THE HANDWRITING AND TREMOR INDICATORS

	YOUNG ADULTS			OLD ADULTS		
Indicator	**Test-retest reliability**			**Test-retest reliability**		
CONTINUOUS	**p-value**	**ICC (95% CI)**	**MDC (SEM)**	**p-value**	**ICC (95% CI)**	**MDC (SEM)**
Tilt_mean [°]	< 0.001	0.96 (0.90-0.98)	2.24 (0.81)	< 0.001	0.99 (0.98-0.99)	2.37 (0.85)
t_{air} [s]	< 0.001	0.93 (0.83-0.97)	0.04 (0.01)	0.001	0.88 (0.57-0.97)	0.08 (0.03)
t_{sheet} [s]	< 0.001	0.96 (0.9-0.98)	0.11 (0.04)	< 0.001	0.96 (0.87-0.99)	0.11 (0.04)
$t_{a/s}$ [a.u.]	< 0.001	0.91 (0.78-0.96)	0.12 (0.04)	< 0.001	0.95 (0.81-0.98)	0.17 (0.06)
$\bar{F}$ [N]	< 0.001	0.88 (0.71-0.95)	1.5 (0.54)	< 0.001	0.96 (0.88-0.96)	2.02 (0.73)
f_{mod} [Hz]	< 0.001	0.80 (0.51-0.92)	0.53 (0.19)	< 0.001	0.68 (0.11-0.91)	1 (0.36)
ApEn [a.u.]	< 0.001	0.90 (0.74-0.95)	0.03 (0.01)	0.002	0.85 (0.47-0.96)	0.08 (0.03)
%RR [a.u.]	< 0.001	0.82 (0.55-0.93)	0.1 (0.04)	0.01	0.77 (0.21-0.94)	0.17 (0.06)
%DET [a.u.]	< 0.001	0.88 (0.72-0.95)	0.06 (0.02)	< 0.001	0.89 (0.60-0.97)	0.06 (0.02)
COUNT	**p-value**	**Kendall's Tau**		**p-value**	**Kendall's Tau**	
NCF [#]	< 0.001	0.85	-	< 0.001	0.88	-
NCA [#]	< 0.001	0.83	-	0.002	0.81	-

Results of the statistical analysis for the test-retest on 20 young adults and 11 older adults. *CI=Confidence Interval. For continuous indicators, test-retest reliability was investigated with Intraclass Correlation Coefficients (ICC), while Kendall's Tau was computed for count indicators.

(increase with age); the couples YY–EE and EY–EE for $t_{a/s}$ (increase with age),%RR, and %DET (increase with age); the couple YY–EE for the $ApEn$ (decrease with age) and Tilt_CV (decrease with age) indicators; the couple EY–EE only for NCF (decrease with age); and the couple YY–EY only for Tilt_mean (decrease with age).

IV. DISCUSSION

This work presents the development, validation, and testing of a smart ink pen instrumented with force and motion sensors, designed for the quantitative and ecological assessment of daily-life handwriting.

The device was designed to autonomously acquire, store, and dispatch data related to the writing gesture. The pen is instrumented with an inertial measurement unit and a miniaturized load cell so that the combined analysis of data collected through these sensors allows the extraction of relevant handwriting and tremor indicators. The smart object features both internal storage capacity and BLE connectivity so that the collected data can be streamed to a remote device either in real time or offline after being stored onboard. To maximize usability and transparency, the pen functioning is self-operated through movement detection or BLE connection request; therefore, no activation button for the end-user is needed; in addition, the sensor data download and processing procedures are automated.

The greatest accomplishment of the devised technology is that it enriches a traditional ink pen with the ability to achieve quantitative reliable handwriting assessment, thus combining the advantages of the digitizing tablet technology with the natural "feel," the ease of use, and the ecological validity of the traditional pen-and-paper approach. These latter characteristics are crucial desires for the end-user, especially when dealing with the elderly population. Indeed, simplicity, intuitiveness, and transparency are key requirements to increase acceptance and reduce the technological anxiety that often characterizes the elderly population [38]. This is even truer when the device is envisaged within the framework of continuous home-based monitoring, as in the case of the proposed technology; the smart ink pen was indeed developed within the European Movecare Project [39], which targets independent older adults living at home with the final aim of detecting early signs of cognitive and physical decline.

The devised smartpen was first successfully validated against gold-standard references. As for the pen load cell, the static tip force measurements calibration using testing weights reported a coefficient of determination extremely close to 1 (0.99), confirming the linearity of the sensor even when constrained in a very tiny space that imposes a pronounced bending of the cable. Comparison of the pen force signal with the reference measurement obtained from an external load cell reported a very strong correlation ($\rho_d = 0.96$) also in dynamic conditions. The validated pen force signal was leveraged for the segmentation of the writing signals into strokes, a critical step of the data analysis process, since the computation of important handwriting indicators relied on it. The validation of the segmentation procedure conducted by comparing the stroke durations obtained from the automatic stroke detection algorithm and the reference segmentation was successful. Indeed, the Bland–Altman plot showed a very good agreement between the two sets of measurements, which were included, for the most part, within the standard deviation boundaries;

TABLE II
AGE-RELATED CHANGES IN HANDWRITING

Indicator	YY (Median	IQR)	EY (Median	IQR)	EE (Median	IQR)	x^2	p-value	YY vs EY (p-value)	YY vs EE (p-value)	EY vs EE (p-value)
Tilt_mean [°]	66.5	9.8	59.1	4.7	60.3	9	10.1	**0.006**	**0.005**	0.59	0.18
Tilt_CV [°]	0.13	0.04	0.16	0.06	0.11	0.03	9.1	**0.01**	0.30	**0.028**	0.07
t_{air} [s]	0.28	0.1	0.40	0.2	0.75	0.46	18.2	**1.1e-4**	**0.013**	**1.4e-4**	0.11
t_{sheet} [s]	0.55	0.25	0.59	0.14	0.63	0.33	0.88	0.64	-	-	-
$t_{a/s}$ [a.u.]	0.47	0.25	0.54	0.17	0.64	0.18	11.8	**0.003**	0.76	**0.002**	**0.04**
$\bar{F}$ [N]	1.87	1.62	1.77	1.50	1.82	1.52	2.8	0.24	-	-	-
NCF [#]	4	3	4	1.25	3	1	6.5	**0.04**	1	0.25	**0.02**
NCA [#]	3	2.25	4	1.5	5	2.5	0.89	0.64	-	-	-
f_{mod} [Hz]	5.2	0.44	5	0.52	4.75	1.22	3.2	0.2	-	-	-
ApEn [a.u.]	1.14	0.09	1.06	0.11	0.9	0.19	16.1	**3.2e-4**	0.08	**1.8e-4**	0.095
%RR [a.u.]	0.39	0.11	0.3	0.1	0.49	0.08	12.9	**0.002**	0.14	**0.02**	**0.004**
%DET [a.u.]	0.74	0.13	0.72	0.15	0.87	0.04	13.5	**0.001**	1	**2.9e-4**	**0.017**

Results of the non-parametric statistical analysis between YY, EY and EE groups. The first p-value reported (column 9) represents the p-value of the Kruskal-Wallis Test, together with the x^2(column 8); for thos indicators that reported a significant p-value in the Kruskal-Wallis Test, pairwise comparisons were conducted through the Wilcoxon Test (Bonferroni adjustment), and the related p-values are reported in columns 10, 11 and 12.

in addition, an almost perfectly linear relation ($R^2 = 0.99$) emerged from the regression analysis between the two sets of stroke durations. As for the pen inertial measurement unit, it was leveraged to estimate the pen tilt angle; the pen tilt was validated through the comparison with a reference angle obtained by means of an optoelectronic system, reporting strong correlation and low error.

After successful validation of the pen sensors and algorithms, the smart object was tested on young and older adults with the twofold aim of testing the reliability of the handwriting and tremor indicators and their sensitivity to distinguish between age groups. Concerning test–retest reliability, results were excellent, with values largely above the 0.75 thresholds of good relative reliability [35], with the exception of the modal frequency for the old adult group, which showed moderate reliability. These high values are even more striking if we consider that the writing content differed between the two trials, importantly suggesting that the reliability of the indicators is independent of the writing content. The MDC was also computed to estimate whether a change between the user's repeated tests represents random variation or a true change in performance. This measure is extremely important to discriminate real changes in the values of the indicators when monitoring users over time, and it is, thus, crucial for the user's longitudinal monitoring to highlight relevant deviations from the standard performance. The reported measurement errors were very low.

Concerning the ability of the writing and tremor indicators to distinguish between different age groups (young adults YY, middle-old adults between 60 and 69 years old EY, and old adults over 70 years EE), our results are mostly in line with previous literature.

As for the temporal handwriting measures, significant age-related changes emerged for the In-air time and the In-air/on-sheet ratio indicators, which increased with age. Our findings confirm previous literature investigating writing copying tasks using digitizers, which reported an increasing trend for these indicators from healthy young to older adults [21] and from healthy older adults to older adults with cognitive decline [6]; moreover, the assessment of in-air time during handwriting was reported to have a major impact on disease classification accuracy in PD [7]. On the other hand, our data showed how the On-sheet time indicator was quite constant over different age groups. As for the indicators related to the handwriting force (Mean writing force), no age differences emerged. For this indicator, contrasting results emerged in previous work analyzing writing copying tasks using digitizers: while no significant association between writing pressure and the frailty phenotype was found by Camicioli *et al.* [9], some studies reported that the writing pressure decreases with age [8] and age-related cognitive pathology [6]. The lack of age-related differences in writing force that emerged from our data is unlikely to depend upon the force resolution of the pen load cell. Indeed, from the static calibration, we obtained a force measurement resolution of 0.02 N, which is two orders of magnitude smaller than the MDC value found for the force signal (equal to 1.5 N). On the other hand, our data showed an effect of age for the NCF within a stroke, which was significantly decreased for the very old group (EE). Our finding confirms the previous literature examining pen-and-paper writing, which reported a more uniform pen pressure for older writers [2].

Concerning tremor, no differences due to age emerged for the modal frequency. While this indicator was shown to be affected by the presence of neurological conditions (e.g., PD) [29], a clear effect of age was not consistently shown in the previous literature, which mainly investigated resting or postural tasks [24], [25], [28], [31]. On the other hand, our data revealed a neat age effect on nonlinear tremor acceleration characteristics. Our results showed a decrease with age of $ApEn$ during handwriting, meaning that more repetitive and predictable tremor oscillation components characterized the older age groups. As for this indicator, the previous literature showed a clear decrease in PD patients [31] and a slightly less evident decreasing trend for older individuals, compared with younger adults, in postural rather than in resting tasks [25], [28], [31]. In line with the $ApEn$ results, the indicators related to the RQA-%RR and %DET presented a significant increase for the very old group (EE), confirming once again the augmented predictability of the tremor characteristics in older writers. Also for these indicators, previous work revealed a marked increasing trend following neurological conditions (PD) [24], while no important changes simply due to older age were consistently demonstrated, at least during postural tasks [24].

To sum up, the results of the writing indicators obtained during free text writing with our pen, especially those related to temporal measures, are in line with the previous literature investigating writing copying tasks with digitizing tablet technology. This result supports our choice of not constraining the writing content or execution in order to increase the ecological validity of the protocol. As for tremor, the nonlinear acceleration characteristics examined in this study while writing with the smartpen present a more marked effect of age compared with the previous work investigating mostly postural tasks [24]. This finding suggests that the study of tremor during more complex activities entailing a blend of cognitive and fine motor skills, such as handwriting, is more effective in bringing out important differences due to aging compared with more simple postural or resting tasks typically investigated in previous work. To this end, the proposed technology, with its combination of force and motion sensors, is key since it allows the simultaneous study of writing and tremor characteristics during handwriting tasks. This important advantage of the smartpen paves the way toward fruitful applications of the current technology in the field of PD. Indeed, signs of the disease include not only tremor but also a series of handwriting abnormalities grouped under the term of "PD dysgraphia" [40], which supports the study of handwriting as a presymptomatic neurobehavioral biomarker of PD [41]. In this framework, it is clear that a technology that allows the combined study of handwriting and tremor features perfectly suits the current needs of the neurological research field. Indeed, the importance of studying handwriting is not restricted to PD but can be extended to a variety of other neurological disorders, including Dyskinesia [42], Huntington's disease [4], and Multiple Sclerosis [43], not only to support the diagnosis process but also to quantify the severity of clinical signs over time and to monitor and manage the risks associated with medications [42]. In addition, a technology that allows quantitative, simple, and ecologically valid evaluation of handwriting finds potential and interesting applications also in the youngest population since handwriting and text production skills assume a central role in the children's development process. In this framework, handwriting difficulties are common in a number of childhood disorders, including, dysgraphia [44], [45], dystonia [46]–[48], and attention deficient hyperactive disorder [49].

In this work, test–retest reliability for the older adults was computed over 11 subjects; future work should enlarge this sample size to compute test–retest reliability on more subgroups of old adults (middle-old and old adults). In addition, more subjects from different age ranges should be recruited to gain more insight into the study of age-related changes of handwriting and tremor from the very young to the old age; to this end, the inclusion criteria should also be carefully defined to avoid confusing factors. The pen force signal considered in this work is the total writing force; future work should also consider leveraging the tilt angle to obtain the force component normal to the writing surface.

V. Conclusion

To conclude, this work presents the development of a smart ink pen instrumented with force and motion sensors, designed for the quantitative and ecological assessment of daily-life handwriting.

The greatest accomplishment of the proposed smartpen is the ability to achieve reliable quantitative assessment of handwriting, without neglecting simplicity and ecological validity. As for quantitative handwriting assessment, different from previous technological solutions, the smart ink pen allows the combined study of writing and tremor characteristics, thus unveiling possible fruitful applications including, but not restricted to, the fields of aging and neurological research. On the other hand, simplicity and ecological validity are key aspects to increase user's technological acceptance and broaden the fields of application to situations in which transparency and ease of use are necessary requirements (e.g., studies targeting older populations, home-based monitoring applications, and clinical studies carried out by nontechnical professionals).

We believe that the proposed smart ink pen represents an important step toward simple, ecologically valid, reliable quantitative assessment of daily-life handwriting, with possible applications in several important health-related fields.

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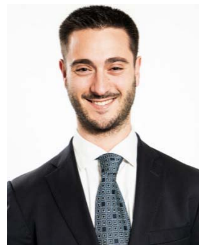

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