

# GyroPen: Gyroscopes for Pen-Input with Mobile Phones

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**Abstract**—We present GyroPen, a method to reconstruct the motion path for pen-like interaction from standard built-in sensors in modern smartphones. The key idea is to reconstruct a representation of the trajectory of the phone’s corner that is touching a writing or drawing surface from the measurements obtained from the phone’s gyroscopes and accelerometers. We propose to directly use the angular trajectory for this reconstruction, which removes the necessity for accurate absolute 3D position estimation, a task that can be difficult using low-cost accelerometers. We connect GyroPen to a handwriting recognition system and perform two proof-of-concept experiments to demonstrate that the reconstruction accuracy of GyroPen is accurate enough to be a promising approach to text entry. In a first experiment, the average novice participant ( $n = 10$ ) was able to write the first word only 37 seconds after the starting to use GyroPen for the first time. In a second experiment, experienced users ( $n = 2$ ) were able to write at the speed of 3-4s for one English word and with a character error rate of 18%.

## I. INTRODUCTION

Small (touch-)screen areas on mobile devices often limit their capabilities for user interaction. In this paper we present GyroPen, a method that brings an experience similar to “drawing with a pen” to mobile devices without using a stylus and without the space restrictions typically imposed by a small form factor. The user can hold the mobile phone like a pen and “write” on any surface (Fig. 1). The trajectory of the phone’s “writing corner” is reconstructed from the phone’s sensors: its gyroscopes and accelerometers. Because the proposed method does not require to use a touchscreen, it is particularly appealing for small form factor devices or for devices lacking a screen.

A promising application of GyroPen’s capabilities is as a method for text entry. Text entry on mobile devices is a topic of interest as mobile devices are getting more popular: entering text on mobile devices is still considered inconvenient by many, although a large variety of input methods have been proposed since the first mobile phones. 12-button phones with predictive text-entry methods (e.g. [1]) have mostly been replaced by touchscreen devices with soft-keyboards. These devices however suffer from the “fat finger problem”, i.e. the fact that a human finger is thicker than a typical key on the virtual keyboard [2] and thus methods for automatic prediction and correction were added, e.g. in the form of gesture-based systems for keyboard entry, e.g. SHARK [3], ShapeWriter [4], and SwiftKey [5]. One of the alternative means of text entry is handwriting, which works naturally with GyroPen input.

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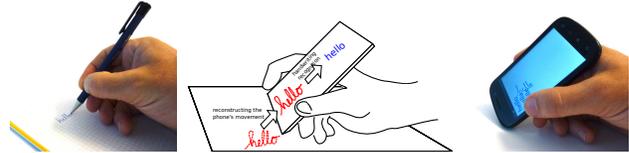


Fig. 1. GyroPen provides a similar experience for writing with a phone as writing with a pen.

## II. RELATED WORK

The idea to use inertial sensors for interaction with mobile devices in general and for text entry in particular has been discussed in the literature before. One of the first reports is [6] in which a pen-device with two accelerometers constructed for the task is combined with a specifically developed writer-dependent HMM recognizer to recognize one of a fixed set of seven words. [7] discusses a similar setup to distinguish ten numerals.

The TiltText approach [8] uses movements of the cell phone to disambiguate among multiple text-candidates when entering text on a 12-button keypad using a low-cost tilt sensor. Similarly Shrimp [9] aims at easing text entry, but instead of relying on a tilt sensor it uses the phone’s camera to estimate its motion using computer vision. Additionally Shrimp improves on the text prediction to allow for entering out-of-vocabulary words more easily.

WalkType [10] helps users to type on a touchscreen while walking. It uses accelerometer data to predict and account for misplaced touch events and corrects the user input with a language model and a model of common typing errors.

Gomez et al. [11] propose a Dasher-like [12] system for text entry controlled by accelerometers.

Approaches that are closely related to ours are PhonePoint-Pen [13] and Airwriting [14]. These systems allow a user to write in the air similar to the process of writing on a blackboard, which requires the user to make fairly large writing gestures in contrast to the small movements required in our approach. Both PhonePoint-Pen and Airwriting use dedicated handwriting recognition systems built for motion-based input. In contrast, our system uses an “off-the-shelf” handwriting recognition system leveraging the efforts of the handwriting recognition community over several decades without further modifications. This is possible because the reconstructed writing paths of our system match how users write with a pen on paper. This has the advantage that recognition can easily be extended to more languages, scripts, and symbols by replacing the recognition backend.

PhonePoint-Pen uses only the accelerometers of a mobile phone and the recognizer is comprised of a manually engineered decision tree and language-model-based correction

to disambiguate likely character confusions. PhonePoint-Pen does not distinguish letter case but supports three editing gestures and numerals. Average character writing times between 3.0 and 4.3 seconds are reported ( $n = 10$ ) and a character error rate of 8.1% for trained users ( $n = 4$ ) and single character input (with the note that “recognition degrades with increasing word-length”). Reference [13] also includes a more in-depth discussion of further related work in this area.

In Airwriting, a specialized motion-sensing device with gyroscopes and accelerometers is attached to the user’s wrist. An HMM-based system is trained on raw sensor data, i.e. the motion path is not reconstructed. A user-independent word error rate of 11% for a fixed vocabulary of 8K words is reported ( $n = 9$ ) [14] for this specific data. The task-dependent training of the Airwriting system requires a sufficient amount of annotated motion data. In contrast, our approach can directly benefit from improvements in normal handwriting systems and thus is easy to extend to new languages.

Miyagawa et al. [15] present a basic system that uses both accelerometers and gyroscopes attached to a pen to reconstruct short writing paths in 3D, but do not evaluate the results quantitatively or specifically for text-entry.

An approach that is similar to ours is the Magic Wand system [16], [17]. The device described in [16] uses both accelerometers and gyroscopes and is specifically constructed to allow 3D trajectory reconstruction. In contrast to our approach, the gyroscopes are mainly used to compensate for gravity and attitude (compare Sec. IV), not directly for the estimation of the writing path (our approach to do so is described in Sec. V). The writing plane is estimated from the 3D motion of the device and the trajectory is projected onto that plane. In contrast, GyroPen supports the use of angular movement only, as it occurs when writing with a pen while resting the palm on a surface. In [16] no recognition is performed but 26+10 Graffiti-style symbols can be distinguished by a human observer from the reconstructed paths. [17] describes an extension in form-factor and a direct integration into a specifically designed gesture recognition system. On a set of 13 gestures designed for easy discrimination by the system, error rates of below 1% are reported ( $n = 15$ ).

The ImuPen [18] similarly estimates motion by double integration of acceleration information with elaborate additional signal processing stages. For writing on a surface, an error rate of 9.6% for a 10-class digit recognition problem is reported in comparison to 2.8% when a digitizer tablet is used. This error rate dropped to 5.4% for writing on an unrestricted surface.

Regarding mobile handwriting recognition in general, it was already available on the Apple Newton [19] but did not become popular until the simplified writing system Graffiti on Palm Pilots [20] and its extensions [21], [22] were available. In modern smart phones and tablets, several handwriting input methods exist [23], [24], [25].

### III. SENSORS

Modern cellphones typically contain three types of motion and orientation sensors: accelerometers, gyroscopes, and a magnetometer.

The *accelerometer* measures the acceleration of the phone in three dimensions (or, equivalently, the forces acting on

the phone). One main component of the measured acceleration is caused by gravitational forces. Additionally, the accelerometer measures any force applied to the phone that results in acceleration. Accelerometers have been built into smart phones for several years, e.g. the first Android phone and the original iPhone already had accelerometers. Most accelerometers built into current devices use the piezoelectric effect. The measurements of an accelerometer are given in  $\frac{m}{s^2}$ .

The *gyroscope* measures rotation about its own three axes. Gyroscopes only became popular in smart phones around the year 2010, e.g. the Nexus S and the iPhone 4 have built-in gyroscopes. Most gyroscopes built into current smart phones use an oscillator to measure the Coriolis effect. The gyroscope measures angular velocity in  $\frac{rad}{s}$ .

The *magnetometer* can be considered a 3D compass that measures the direction of the magnetic field at the current location. Magnetometers have also been built into mobile phones since the first generation of smart phones. Most magnetometers in cell phones directly measure the magnetic field using the Hall effect. Unfortunately (for the use in low-latency applications) magnetometers are often slow. The measurements of a magnetometer are given in  $\mu T$ .

In our approaches described below we generally poll the measurements of all sensors with a frequency of about 150Hz which we found to be sufficient to capture writing movements while balancing the tradeoff for low energy consumption.

### IV. ACCELEROMETER-BASED APPROACH

The first approach to reconstructing the motion of a mobile phone that comes to mind uses the accelerometers and (double) integrates over their measurements.

The accelerometer measures the acceleration of the phone in three dimensions  $a = (a_x, a_y, a_z)$ . When the phone is held still with respect to the user in static conditions, the accelerometers only measure gravity  $g = (g_x, g_y, g_z)$ , which is typically  $|g| = 9.81 \frac{m}{s^2}$ . Once the gravity is estimated, the vector  $a$  can be rotated into a vector  $a' = (a'_x, a'_y, a'_z)$ , where the  $z$ -axis points in the opposite direction of the gravity and thus the directions of  $a_x$  and  $a_y$  are parallel to the desired horizontal writing plane. Thus, discarding the  $z$  component after rotation effectively eliminates  $g$ , which is usually the strongest force in the accelerometer measurements.

With these rotated observations, we start from a hypothetical starting point  $(x_0, y_0)$  and compute the position  $(x_N, y_N)$  of the phone after  $N$  sensor readings as

$$(x_N, y_N) = (x_0, y_0) + \sum_{n=1}^N \Delta t_n (v_{nx}, v_{ny}) \quad (1)$$

with

$$(v_{nx}, v_{ny}) = (0, 0) + \sum_{i=1}^n \Delta t_i (a'_{ix}, a'_{iy}). \quad (2)$$

where  $\Delta t_n$  is the time that passed between measurements  $n - 1$  and  $n$ . While this approach is appealing in theory, it turns out that in practice the double integral (or sum) is very sensitive to noise and the sensors built into current phones are often too noisy to give sufficiently precise readings for accurate estimation of a writing path. Airwriting [14]

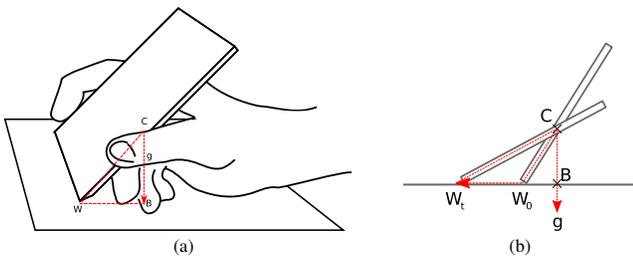


Fig. 2. Writing with the phone. (a) The hand is holding the phone like a pen. To determine which words the user writes, we measure the rotation around point  $C$  and estimate at which point  $W$  the phone touches the writing surface. (b) Simplified to two dimensions, the writing point  $W$  moves as the phone rotates and translates.

avoids this problem by (a) not reconstructing the writing path explicitly but training the handwriting recognizer on sensor data directly and (b) using a high-accuracy sensor unit which is more expensive than the manufacturing price of current smart-phones.

## V. GYROPEN: GYROSCOPE-BASED APPROACH

GyroPen allows for writing with the phone like a user normally would write with a pen<sup>1</sup>. Most movements of a pen while writing are performed without actually moving the entire hand. Instead, the writing motion of the pen tip results from moving the pen using mostly finger and wrist movements. This motion consists to a large part of rotations. Then, occasionally the entire hand is moved by just a few centimeters, e.g. to start a new word or line.

GyroPen uses the phone's gyroscopes to estimate the motion of the writing point. The gyroscopes directly measure angular *velocity* about three axes  $r = (r_x, r_y, r_z)$  and thus a single integration will be sufficient to determine how far the phone was rotated. Starting from an initial attitude of the phone  $o_0 = (o_{0x}, o_{0y}, o_{0z})$ , which is initialized from a gravity estimate while the phone is held still, we update the attitude estimate by rotating it according to the gyroscope measurements.

The motion of the phone's writing point  $W$  is approximated by assuming that the overall motion consists of a rotation around a fixed virtual center point  $C$  and a translation of the pen along the line  $C-W$  such that  $W$  continuously touches the surface (Fig. 2). For different users the point  $C$  may be at different locations depending on how they hold the phone. Considering the 2D case in Fig 2b, the user rotates the phone such that the writing point  $W$  moves from  $W_0$  to  $W_t$  and continuously shifts the phone such that  $W$  touches the writing surface. Under these assumptions, the phone's attitude (as determined from the gyroscopes) is sufficient to determine the writing motion trajectory from  $W_0$  to  $W_t$ . During writing, the position of  $C$  may vary, but for smooth motion this will not lead to large distortions.

$g$  is the direction of gravity and we assume the distance between points  $B$  and  $C$  (the distance of  $C$  from the writing surface) to be approximately 5cm. Note that the exact distance between these points does not influence the nature of the recorded handwriting but only changes a fixed scaling factor

<sup>1</sup>See the video in our supplementary material for a comparison how a user writes with a pen and with GyroPen.

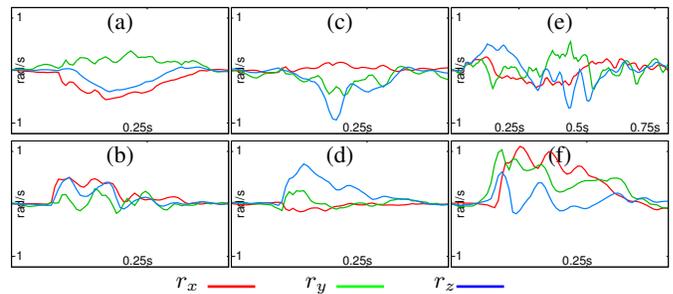


Fig. 3. Measurements from the gyroscope while performing different writing strokes in  $\frac{rad}{s}$  over time. (a) "left to right" (b) "right to left" (c) "bottom up" (d) "top down" (e) "circle" (f) "pen up".

that is applied to the reconstructed trajectory. The handwriting system may later apply an extra size normalization (we do not pass on any writing area sizes) and thus the recognition accuracy is invariant with respect to the writing size (Sec. V-F).

Note that this approach can be extended to larger movements typical for say writing with a laser pointer (Sec. V-E). It also works well when restricting the writing to a very small area: restricting the writing area to a band of height 5mm was found to be unproblematic for recognition.

### A. Initialization

For initialization we determine the initial attitude  $o_0$  of the phone while it is not moving using the accelerometer. We estimate gravity  $g$  from  $N$  accelerometer measurements while the phone is not moving which gives us a reliable estimate of our initial attitude  $o_0$  (up to a rotation about the vertical axis). During the implementation of the system we experimented with different values for  $N$  and found that  $N = 10$  is a suitable choice. This means that the initialization only takes a fraction of a second and it is a good compromise between a stable estimate for gravity and waiting for the initialization.

### B. Tracking movements

To update the phone's attitude as it rotates we use the gyroscope measurements. From the sequence of phone attitudes we compute the trajectory of the phone's writing point  $W$  on the writing surface.

We use quaternions as a convenient way to describe and work with rotations in 3D space. When we say that we update an attitude  $o_1$  using an angular velocity  $r$ , we first determine the angle  $Q(\Delta t \cdot r)$  by which the phone was rotated from  $r$  and the time  $\Delta t$  corresponding to this measurement. Then, we compute the updated attitude  $o_2$  by rotating  $o_1$  by that angle

$$o_2 = o_1 * Q(\Delta t \cdot r). \quad (3)$$

where  $*$  is the quaternion multiplication which corresponds to rotating  $o_1$  by the angle  $\Delta t \cdot r$ .

This is performed for every measured angular velocity  $r_t$  successively. Then we compute the location at which point  $W$  touches the writing surface for every time step  $t$ , assuming the writing surface is orthogonal to the gravity vector  $g$  and cutting it at point  $B$ .

Figure 3 shows the output of the gyroscope sensor while different writing movements are performed. It can clearly be seen that writing into different directions creates distinct

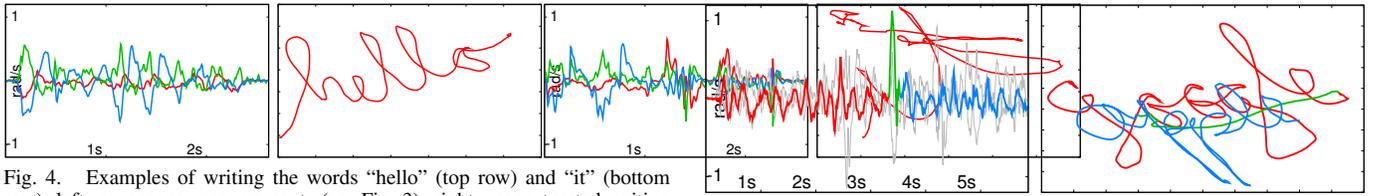


Fig. 4. Examples of writing the words “hello” (top row) and “it” (bottom row). left: gyroscope measurements (cp. Fig. 3); right: reconstructed writing path.

gyroscope measurements. However, it is also clearly visible that raising the writing point  $W$  above the writing surface (Fig. 3(f)) has a very similar pattern to a “right to left” movement (Fig. 3(b)). In both cases, the  $r_x$  value goes up strongly and stays high for the entire movement, the  $r_y$  and  $r_z$  values show a wave pattern. The biggest difference between these two movements in our plots is the magnitude of the measurements which is not intrinsic to the movement direction but only depends on the movement speed. Therefore, we decided not to handle “pen up” movements explicitly but trace the movements over the entire time and handle the “pen up” strokes (i.e. the strokes that were reconstructed but which are not intentionally written strokes) at a later stage.

Fig. 4 shows examples of reconstructed writing paths for the two words “hello” and “it”, both of which are legible to humans. In the path for “it”, the pen-up problem is clearly visible: the delayed strokes (i.e. the t-stroke and the i-dot) are connected to the previously written strokes.

### C. New-word heuristic

With the method described above it is possible to write in an area of about  $7 \times 5$  cm without moving the hand on the writing surface. This area is sufficiently large to allow for writing sizes similar to results of writing with a pen on paper. When writing with a pen, a user occasionally moves their hand forward to be able to keep writing in a line. Here, moving the hand forward is not necessary. Instead, the hand can remain at the same spot while writing multiple words (or word-parts) on top of each other: when the end of a word is reached, the user lifts the writing corner, moves it to the left, and then writes the next word “over” the previous one.

To detect this restart gesture we apply a straightforward decision rule based on the measurement  $r_x$  of the gyroscope of rotation around the phone’s  $x$ -axis, where the combined signals for “pen up” (Fig. 3(f)) and “right to left” (Fig. 3(b)) leads to a characteristic pattern (Fig. 5) which allows detection of the restarts and segmentation of the writing into three parts:  $w_i$  the first word,  $\xi_i$  the restart gesture which is discarded, and  $w_{i+1}$  the second word.

$w_i$  contains all sensor measurements from the beginning (or from the end of  $\xi_{i-1}$ ) until  $r_x$  exceeds a threshold  $\theta_u$ . Starting from there, all observations that exceed a threshold  $\theta_l$  are considered to be part of the restart gesture  $\xi_i$  and once the  $r_x$  drops below threshold  $\theta_l$  the next word  $w_{i+1}$  starts. The thresholds were chosen to be  $\theta_u = 0.6$  and  $\theta_l = 0.2$  from analyzing multiple graphs similar to Fig. 5 during the initial implementation of this method and ahead of any of our user studies.

Fig. 5. The sensor output of the gyroscope  $r_x$  when writing the word “google”, then moving the phone back to the beginning, and then writing “apple” at the same location and the reconstructed writing path. The colors encode the recognized words:  $w_1$  in red, the restart gesture  $\xi_1$  in green, and  $w_2$  in blue. In gray, the gyroscope reading for  $r_y$  and  $r_z$ .

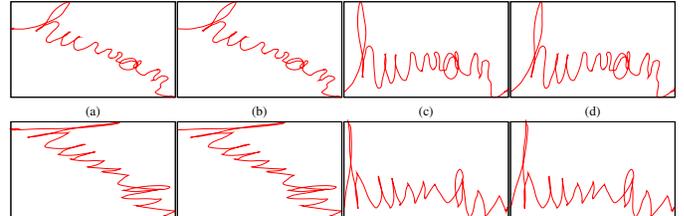


Fig. 6. Postprocessing steps. Writing paths from two different users going through the post-processing pipeline: (a) reconstructed writing path; (b) after start-stop detection; (c) after slope correction; (d) after slant correction.

### D. Postprocessing

After the writing path has been reconstructed, we perform several post-processing steps to make the recovered writing paths more similar to normal handwriting and to reduce differences between the writing styles of different users.

1) *Start/stop detection*: Our system requires the phone to be held still while the gravity vector is estimated, but holding the pen stationary is unusual in handwriting data. Similarly, the end of the input is signaled by holding the phone still for half a second. Removing these pauses in the phone motion improves handwriting recognition because it makes the output of GyroPen more like normal handwriting input for which the handwriting recognition system was optimized.

For start-detection, we drop all observations until the distance between two consecutive points exceeds a threshold  $\theta_s$ . For the stop-detection, we wait until the phone has been still for half a second by detecting that no two consecutive points have a distance exceeding the threshold  $\theta_s = 0.04$  for 500ms.

While the difference is not visually apparent (Fig. 6(a) and (b)), the start-stop detection removes between 10 and 50 similar points on most samples at the beginning and end.

2) *Slope correction*: Due to different users holding the phone at different angles, the recovered writing paths have different slopes (Fig. 6(b)).

To improve recognition, we normalize the slope by measuring the angle  $\phi_w$  between the first and the last point of each written word  $w$ ; averaging over the written words; and rotating the words toward the horizontal by this angle (Fig. 6(c)). Note that this heuristic is very simplistic and more elaborate techniques are likely to further improve the accuracy of the overall system (see Fig. 11).

3) *Slant correction*: After the slope correction, we apply a slant correction to normalize the writing paths. In normal handwriting of Latin-script languages, the most common directions are vertical (or near-vertical) strokes, such as the letter “I” or the first and the last part of the letter “M”.

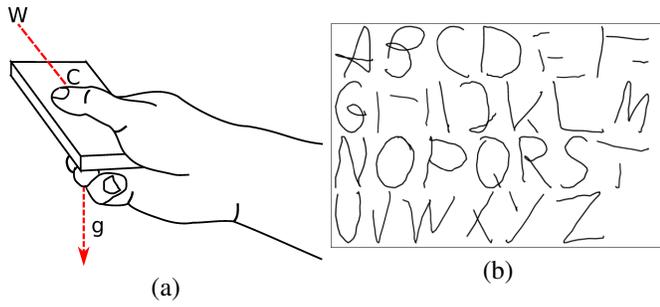


Fig. 7. (a) Laser pointer mode and (b) examples of uppercase letters written using the laser pointer mode.

Also here, different users tend to write with different slants (Fig. 6(c)). In order to normalize for slant, we compute a histogram of directions for each stroke by computing the deltas between every pair of points between pen-down and pen-up events, determine the dominant direction and then apply a shear transform to align it to the vertical (Fig. 6(d)).

### E. Laser pointer mode

One further advantage of the gyroscope-based approach is that it easily transfers to a “laser pointer”-like writing mode where we assume the writing point  $W$  to be on the extension of the phone’s longer dimension (Fig. 7a). In this case, the hypothetical distance between the points  $C$  and the point  $W$  determines the scale factor of the trajectory.

This mode turns out to be useful for interaction with home cinema systems, similar to the touch pad on recent Sony settop boxes [26], and the phone motion can either be used to control a cursor or to handwrite characters. Handwriting can be activated by pressing and holding a button (physical or on the touchscreen), similar to the interaction model of a laser pointer. Fig. 7b shows one example of each of the 26 English uppercase letters written using the laserpointer mode.

### F. Handwriting recognition

To recognize the written items, we use an online handwriting recognition system similar to the one used in the Apple Newton [19] but using an extended feature set similar to the NPen++ recognizer [27]. In online handwriting recognition, the input to the system is a trajectory of  $(x, y)$  coordinates over time  $t$ . The handwriting recognition engine used was built for normal online handwriting data aiming to recognize stylus input and writing with a finger on a touchscreen. Its recognition accuracy is comparable to other state-of-the-art online handwriting recognition systems. Note, that in contrast to other systems (e.g. 8000 words in [14], 13 gestures in [17]) the handwriting recognition system is an open vocabulary recognizer that can recognize any word that can be written with its alphabet independently of whether it is a proper word and whether the system has ever seen it in the past. To evaluate this, we tried to write the authors’ last names and found this to be easily possible.

Above we mentioned that GyroPen does not handle pen-up movements explicitly but considers them to be part of the writing motion. To handle such strokes, the online handwriting recognition literature has been using pen-up strokes as part of

the observation [27]. Pen-up strokes also have been used as a means to make models for Chinese handwriting recognition invariant to printed and cursive writing styles [28].

The handwriting recognition system performs size and writing-speed normalization and therefore the writing size and speed of a particular item has no impact on the recognition.

### G. Calibration

As every sensor (even of the same type) behaves slightly differently, we perform a phone-specific calibration. This has to be performed once per phone and only takes a few minutes. With this calibration we aim to account for sensor-specific noise and scale so that we can compute calibrated sensor readings  $s^c$  from the raw sensor readings  $s^r$  and offset  $O$  as  $s^c = S \cdot s^r + O$ .

For both, the gyroscopes and the accelerometers we want to compute the calibrated 3-dimensional vectors as

$$\begin{pmatrix} s_x^c \\ s_y^c \\ s_z^c \end{pmatrix} = \begin{pmatrix} S_x & 0 & 0 \\ 0 & S_y & 0 \\ 0 & 0 & S_z \end{pmatrix} \cdot \begin{pmatrix} s_x^r \\ s_y^r \\ s_z^r \end{pmatrix} + \begin{pmatrix} O_x \\ O_y \\ O_z \end{pmatrix} \quad (4)$$

In the following we describe how the parameters  $S$  and  $O$  are determined for the accelerometers and gyroscopes.

1) *Accelerometers*: For the accelerometers we can estimate the offset and the scale jointly. To estimate the offset and the scale, we record a total of  $I$  accelerometer measurements  $a_1, \dots, a_I$  in at least three different positions while the phone is not moving. Using the assumption that the phone should measure an acceleration of  $g = 9.81 \frac{m}{s^2}$  while the phone is still and given our error model (eq. (4)), we can compute the parameters  $S$  and  $O$  using a system of  $3 \cdot I$  linear equations

$$\left[ a_i^c = S a_i^r + O \right]_{i=1}^I \quad (5)$$

where we approximate the calibrated measurement as  $a^c = 9.81 \cdot a^r / \|a^r\|$ .

Note that this assumes that the scale for each dimension is the same and that the offset is small. In practice this is not always true, but we validated the assumption by estimating the scale of the axes when the entire gravity components was on a single axis, which suggested that the approximation is appropriate.

Then, we solve this system for the entries of the diagonal matrix  $S$  and the offset vector  $O$  using the pseudo-inverse of the expanded equation system.

For the accelerometers of our experiment phones we found the scale to be in the range between 0.9 and 1.1 and the offset to be between  $-0.1 \frac{m}{s^2}$  and  $0.1 \frac{m}{s^2}$ .

2) *Gyroscopes*: To estimate the scale  $S$  and the offset  $O$  for the gyroscope we apply a two step procedure: first we estimate  $O$ , then  $S$ . For convenience, we change the error model of the gyroscope to  $r^c = S(r^r + O)$  which is equivalent to eq. (4) but simplifies notation.

An ideal gyroscope will measure no angular velocity when not in motion. To estimate the offsets  $(O_x, O_y, O_z)$  we therefore record  $M$  gyroscope measurements while holding the

phone still. Then, we compute the average over these and set the offset to be

$$(O_x, O_y, O_z) = -\frac{1}{M} \sum_{m=1}^M (r_x, r_y, r_z). \quad (6)$$

To compute the scale of the gyroscopes we would ideally know the output of the gyroscope while the phone performs a rotation for which we know the ideal output for every step. We approximate this by asking the user to move the phone in a series of rotations about each axis in turn, starting and stopping at the same spot. Then, we record the timestamp pairs for which the phone has the same attitude as detected using the phone's 3D compass.

We record a sequence of  $I$  gyroscope  $r$  and compass  $m$  measurements  $(r_1, m_1), \dots, (r_i, m_i)$ . Then we detect pairs  $(i, j)$  with  $i < j$  where  $m_i = m_j$  for a pair of time indices. These pairs represent points where the user has completed a rotation and is holding the phone still. We know that at these two time steps, pairs  $(o_i, o_j)$  should be identical.  $o_j$  can be estimated as (compare with eq. (3))

$$o_j = o_i \underset{n=i}{*}^j Q(\Delta t \cdot r_n). \quad (7)$$

This allows us to assess how much our estimated attitudes  $o_j$  differ from their expected attitudes  $o_i$  on average:

$$\sum_{(o_i, o_j)} d(o_i, o_j) \quad (8)$$

where  $d(o_i, o_j)$  measures the angle between  $o_i$  and  $o_j$ .

Then, we use the Downhill-Simplex method [29] to minimize eq. (8) starting with an initial identity matrix for  $S_r$ .

For the gyroscopes of our experiment phones we found the scale to be in the range between 0.9 and 1.1 and the offset to be between  $-0.01 \frac{\text{rad}}{\text{s}}$  and  $0.01 \frac{\text{rad}}{\text{s}}$ .

3) *Evaluating the calibration parameters:* We evaluate our calibration methods by computing the calibration criterion for two different sets of calibration measurements. For the accelerometer calibration, the criterion is the sum of squared error of the system of linear equations (eq. (5)), for the gyroscopes calibration, the criterion is given in eq. (8).

For the experiments we recorded two calibration measurements for the accelerometer and the gyroscope on different days. Then we estimated the calibration parameters  $S$  and  $O$  independently for the two measurements and evaluated the criterion on the respective other.

The experiments show that the calibration procedure works for both accelerometers and gyroscopes (Table I). The estimated calibration parameters for both sequences are significantly better (lower) than using no calibration at all (top row).

## VI. EVALUATION

For the experiments we used two different devices: a Samsung Galaxy Nexus and a Samsung Nexus S. These contain an Invensense MPU-3050 motion sensing unit and an EM-Tech EME1511AFRC module including a motion sensor, respectively. Both are low-powered motion-sensing units and during the experiments for the paper we did not observe any additional power drain on the batteries of the used devices.

TABLE I

QUANTITATIVE EVALUATION OF THE CRITERION. THE CALIBRATION CRITERION FOR BOTH ACCELEROMETERS AND GYROSCOPES IS GIVEN FOR TWO MEASUREMENTS. CALIBRATION 1 AND 2 WERE ESTIMATED ON THE MEASUREMENTS 1 AND 2, RESPECTIVELY.

	accelerometer		gyroscope	
	1	2	1	2
$S = \begin{pmatrix} 1 & & \\ & 1 & \\ & & 1 \end{pmatrix}, O = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}$	0.257	0.387	0.022	0.0118
calibration 1	0.179	0.225	0.019	0.0033
calibration 2	0.205	0.190	0.020	0.0021

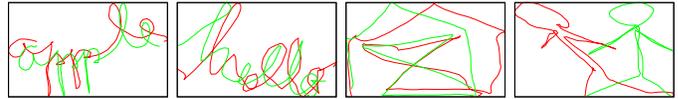


Fig. 8. Comparison of the reconstructed writing paths and the aligned groundtruth paths. Red: the reconstructed path from GyroPen, Green: the groundtruth path from the graphic tablet.

Additionally, we performed informal experiments with four other popular Android smartphones (LG Nexus 4, Samsung Galaxy S3, Sony Xperia LT26i, HTC One X) to verify that the proposed methods are not over-optimized for the test devices. On each of these devices, the GyroPen prototype worked without any changes.

### A. Evaluation of reconstruction accuracy

To evaluate the accuracy of the writing path reconstruction we performed experiments recording both the reconstructed writing path as well as the actual writing path of the phone's writing point simultaneously. To record the actual writing path, we used a Wacom Bamboo Pen & Touch graphic tablet and fixed its stylus to the phone using sticky tape. With this setup we recorded a dataset of 13 words and drawings<sup>2</sup> compared the reconstructed paths from GyroPen to the groundtruth paths from the tablet.

To measure the reconstruction error we aligned both paths using a dynamic programming algorithm similar to the one used for stereo reconstruction [30] and measured the error between the reconstructed and the recorded path. The experiments showed an average deviation between our reconstruction and the ground truth of less than 4% relative (5% standard deviation) to the length of the path. The highest error was observed for one of our small drawings where slant correction went wrong (15%).

Four examples comparing the reconstructed paths are shown in Fig. 8. For the first three examples, the paths were aligned very well. In the bottom-right example, the slant correction built into GyroPen failed because it was designed with handwriting in mind and thus the stickfigure drawn with GyroPen is strongly slanted to the left. Thus, when using GyroPen for drawing it is advisable to disable the slant correction.

### B. User study: learning to use GyroPen

We assessed how quickly a novice user of GyroPen is able to use it for writing a few simple words in a proof-of-concept experiment. For this, we conducted a small user study with 10

<sup>2</sup>apple, C, d, google, hello (3x), programming, house drawing (3x), stick figure drawing, heart drawing

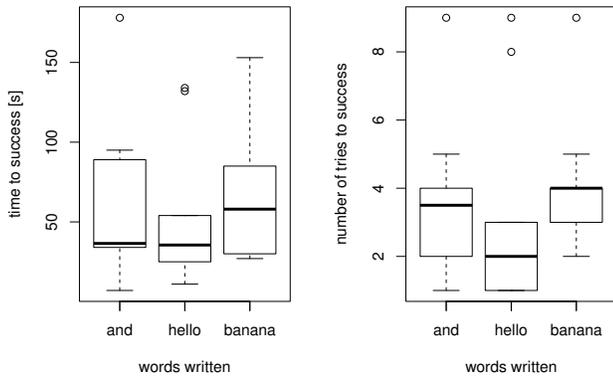


Fig. 9. Distribution of (a) writing times (in seconds) and (b) number of tries necessary until success as box-and-whisker plots. The bold line gives the median values, the lower and upper boundaries of the box mark the 25% and 75% quantiles. The whiskers give the minimal and maximal measured values and the circles mark outliers.

volunteers who had never used the GyroPen prototype before and had no insight into how it works. The participants, all employed at the same company as the authors of this paper at the time of the study, were aged between 20 and 40 years and both male (9) and female (1). There were 2 left-handed and 8 right-handed participants. The study was conducted using the following script and lasted about 15 minutes per participant. The prototype was running on a Samsung Nexus S phone.

- **Introduction** We gave a short introduction how GyroPen can be used and demonstrated writing a few words.
- **Writing** We asked the users to try to write three strings of increasing length and difficulty: (1) “and”, (2) “hello”, (3) “banana”. To get an objective measurement of the entire system’s performance, we asked the participants to continue trying to write these strings until the system recognized the string. We limited the number of tries to ten times, and recorded the number of tries and the time it took each participant.
- **Questions** We asked the participants a series of fixed questions, starting by having them rate the experience with respect to “interestingness and novelty” on a scale from 1-10. Then we asked them for positive and negative adjectives, whether they would install a GyroPen app and if they saw specific circumstances in which the method could be particularly useful.

1) *Quantitative evaluation:* Figure 9 shows the distribution of writing times and number of tries necessary for the study participants to write each word. The variation in these measurements is very large. This shows that different users have a varying degree of difficulty adapting their natural writing movements.

The average participant was able to write the first short word after half a minute, then a longer one after about the same time and then took about one minute to write the six-letter word “banana”. (The median times are 36.5s, 35.5s, and 58.0s, respectively.)

The median number of tries for each test word were 3.5, 2, and 4, respectively. This suggests that the participants got used to this new way of writing quickly and could write the second word with few attempts, but then needed more attempts for the

third, longer (and probably also harder to recognize) word.

Note that these times are measured up to the point that the trajectory could be interpreted correctly by the handwriting recognition system – the reconstructed and visualized text was readable for a human typically much earlier. The median number of tries until a human could read the test words was 1.5, 1.0, and 2.5 (compared to 3.5, 2.0, and 4.0 which we report for machine recognition, Fig. 9). This means that when used for the purpose of just taking a note in a graphical format (just storing the sketch, not requiring recognition) the approach could deliver results much faster than the values above suggest (compare also the study in Sec. VI-C which shows that experienced users need 3-4s to write a word).

The outliers towards the longer times and number of tries show that this input method will probably not be the method of choice for fast text entry for everybody, but similar restrictions apply for other input methods, like e.g. speech input or handwriting using a stylus.

On the other hand, some participants were able to input the desired word very quickly and with only few attempts. This is despite the fact that most of the participants started the study with stating that they had a “terrible handwriting”.

In summary, we consider the results of this experiment to be very promising since they indicate that new users will be able to use GyroPen quickly and without much help. For more reliable results it would be necessary to perform a large study with more users and more words.

2) *Qualitative evaluation:* The study participants rated the interestingness and novelty of the approach on average (mean=median) with a score of 8 out of 10. Note that the source of participants makes it likely that there is some bias in these results, but we feel that they are an interesting summary of the voiced opinions.

Prompted for positive impressions, the participants responded with these and similar assessments: surprised it works and recognized my handwriting, amazing, awesome, new, interesting, cool idea, intuitive, interesting, has potential, cool and fun, innovative, natural, wonderful idea, much better than handwriting on a touchscreen, definitely better than voice recognition.

Prompted for negative impressions, the participants responded with these and similar assessments: smartphone is bulky/clunky/big, maybe as a standalone pen it could work better, need to improve moving the hand, needs a surface, awkward to hold the phone like this, difficult for long words, cannot beat speed of other input methods for me, there’s a learning curve, quality needs to be improved, a bit difficult.

When asked about situations in which this input method could be particularly useful, the answers included: taking of digital notes quickly (with and without handwriting recognition), e.g. in school or for a quick note; when too noisy for speech recognition; when using the touchscreen is difficult (wet or sticky fingers); for storing sketches; just on a pen that is paired with a smart-phone; recording signatures; kids’ drawings.

While the absolute writing area of the GyroPen approach is about the same size as a phone screen, the thickness of fingers makes it difficult to write as small as with GyroPen. Therefore, users had the impression that with GyroPen there

is more space. The high accuracy of GyroPen easily allows writing with a letter height of about 5mm. This is smaller than most people can write with their finger tip on a touchscreen.

In summary, while there is certainly room for improvement, most participants viewed GyroPen as an interesting and promising application.

### C. User study: writing the full alphabet

To evaluate more parameters of the proposed input method, we performed a second experiment with two users who had used the GyroPen system in the past and had a good understanding of how it works.

In this experiment the task was to write 26 common English words<sup>3</sup>, one starting with each letter of the English alphabet, both starting in lower and upper case. The users were asked to write each of the 52 words ten times in sequence with GyroPen. During this experiment we measured the character error rate (CER) (Fig. 10) and writing speed. For comparison, we also asked the users to write each word once with a finger on a touchscreen for normal handwriting recognition.

During this experiment both users improved their writing skills: when writing a word for the first time, the users had about 40% CER. The CER dropped to about 28% in the second trial, and after ten trials the users averaged at about 18% CER. For comparison the same users obtained between 5% and 7% CER when using normal handwriting. This suggests that some of the errors that users make are due to an imperfect recognition system but that a certain amount of errors are introduced through using GyroPen. As the handwriting recognition system was trained on conventional handwriting input, we suspect that this gap could be closed further by (a) adding GyroPen training data to the recognition system or (b) adjusting the GyroPen reconstruction to let the output resemble conventional handwriting even more, or both.

Regarding writing speed, user 1 needed an average of 3.6s to write each word, user 2's average was 3.1s. In comparison, using normal handwriting input both users needed slightly more than 1s to write the words on average. The measurements show no significant change in writing speed during the ten trials.

We also analyzed a potential dependence between the error rate and the writing speed by measuring the correlation between normalized writing speed (per word per user) and CER and found a correlation coefficient of 0.07, which indicates that the dependence is very small if there is a dependence at all. The same result is obtained when comparing the average CER on words that were written faster than the median speed (per word per user) which is the same as the CER on words that were written slower up to the third significant digit. Note however, that these experiments have been performed with just two users and thus the results may not hold in a large user study.

Fig. 11 shows a comparison of normal writing styles of the two users with their writing styles using GyroPen for selected words. It is interesting to observe that some of the characteristics of the users' handwriting styles are preserved,

<sup>3</sup>and; been; can; day; even; for; game; have; issue; job; know; long; more; new; one; play; quick; run; some; the; under; very; was; xenon; year; zone

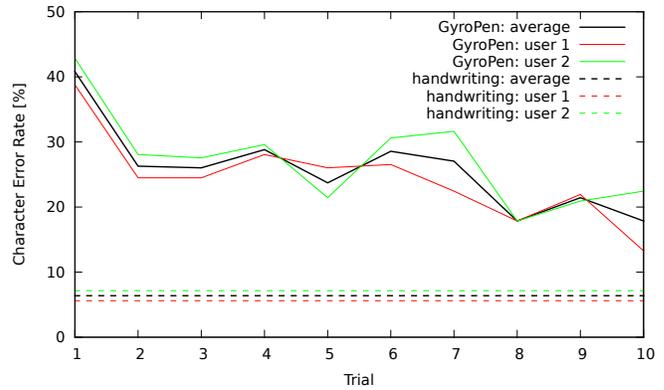


Fig. 10. Average CER for the ten trials of writing the 52 words for the second user study.

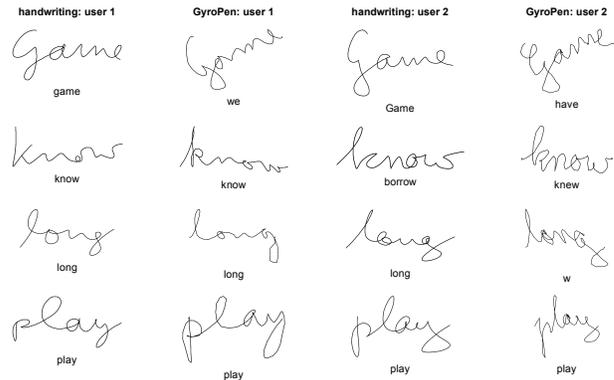


Fig. 11. Writing styles of two users using normal handwriting on a mobile phone touchscreen and using GyroPen. The recognition result of the handwriting recognition system is shown under the samples.

e.g. the characteristic shapes of the loops in 'g' and 'y' seem to differ more between writers than between recording methods.

Further, the examples show how the handwriting recognition system makes some mistakes on GyroPen samples that are clearly legible for a human. We suspect the difference to be due to increased slant and slope of the recorded samples and also partially due to a missing reference frame.

### D. Non-Latin script input

To evaluate if the GyroPen approach is applicable to other scripts, we performed the following experiment: We switched the handwriting recognizer language to Chinese and tried to write a few Chinese characters. Recognizing these characters worked surprisingly well using a cursive writing style. We did not need to apply any additional tuning except disabling the slope correction. Examples of writing trajectories and recognized characters are shown in Fig. 12.

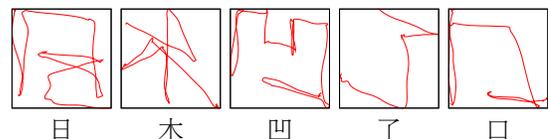


Fig. 12. Writing Chinese characters. Reconstructed writing paths (top) and recognition results of the Chinese handwriting recognition engine (bottom).

## VII. CONCLUSION & OUTLOOK

We have presented GyroPen, a method that reconstructs a user's writing path from the inertial sensors of a phone and have shown that this is a promising approach toward handwriting with the phone. We describe the approaches used for high-accuracy writing-path reconstruction and show that the reconstructed writing paths are accurate enough to be recognized by an off-the-shelf handwriting recognition engine without the need for special tuning. In a first proof-of-concept experiment the majority of the participants reacted positively to the approach and could use it after a learning period of just a few minutes. In a second experiment we observed that the method can be used to write all letters with acceptable accuracy after some practice. We have shown that the system is an interesting prototype aiming to enable handwriting with the phone rather than on the phone for an intuitive experience for text entry into mobile phones which will open unique applications in the future.

GyroPen could be improved by explicitly handling pen-up strokes, for instance using a sensor-fusion approach of gyroscopes and accelerometers or by training a handwriting recognition system that is fully invariant to pen-up strokes.

The proposed method has the advantage that it works on smart phones without any modification to the hardware. If it was possible to add additional sensors to the phones, a similar user experience could be obtained e.g. by building a small trackball or an optical mouse sensor into the phones writing corner. Another alternative to using the inertial sensors would be to use computer vision techniques with the built-in camera to reconstruct the phone movements similar to TinyMotion [31]. This would also work without additional sensors but might be problematic if the writing surface is very homogeneous and thus there would be no features to track.

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