Eliciting Pen-Holding Postures for General Input with Suitability for EMG Armband Detection

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ABSTRACT

We conduct a two-part study to better understand pen grip postures for general input like mode switching and command invocation. The first part of the study asks participants what variations of their normal pen grip posture they might use, without any specific consideration for sensing capabilities. The second part evaluates three of their suggested postures with an additional set of six postures designed for the sensing capabilities of a consumer EMG armband. Results show that grips considered normal and mature, such as the dynamic tripod and the dynamic quadrupod, are the best candidates for pen-grip based interaction, followed by finger-on-pen postures and grips using pen tilt. A convolutional neural network trained on EMG data gathered during the study yields above 70% within-participant recognition accuracy for common sets of five postures and above 80% for three-posture subsets. Based on the results, we propose design guidelines for pen interaction using variations of grip postures.

Author Keywords

Pen input; touch input; mode switching; EMG.

INTRODUCTION

The pen is a popular input method to write, draw, and perform precision tasks on a tablet. Most applications require input methods to switch between pen "modes" (e.g. inking, selection, erasing, scrolling) and to invoke commands like adjusting mode attributes (e.g. thickness, colour, brush type) [21]. In traditional pen interfaces, this is accomplished with graphical widgets, but this can be slow [8,39]. In response, new interaction techniques to increase pen input efficiency vocabulary have been suggested, such as bimanual pen and touch interaction [1,10,13,24,45] and adding sensing capabilities to the pen and the tablet [11,33,48].

One interesting category of techniques maps input modes to different pen grips [2,12,33,36,37]. For instance, when the user uses their normal pen-holding posture, a default mode like inking is active. To trigger a different mode or interface action, the user temporarily changes the way they hold the pen, such as extending a finger to touch the tablet in order to erase [2]. The advantage of such techniques is that they only involve the pen-writing hand, making them suitable for small tablets and situations when the other hand is occupied (like holding the tablet itself). The main disadvantages when using the pen-holding hand for input actions is increased dexterity requirements and reduced comfort [2].

In all prior work exploring alternative pen-holding techniques, the authors propose different grips that can be detected by their sensing equipment and assess their suitability with participants *a posteriori*. However, handwriting poses vary between individuals [7,32] and likely even more so for intentionally chosen grip variations. People might have very different preferences about what kind of alternative postures and pen manipulations they would be willing to adopt for explicit input actions. Such *a priori* knowledge of user preferences to justify the choice of using variations in pen grip postures for input has not been investigated. On the technology side, sensing techniques used for pen-grip recognition are mostly based on touch or grip patterns detected by sensors embedded in the pen or in the tablet [2,12,33,36,37]. This precludes potentially useful gestures that cannot be detected by such sensors, like mid-air hand and finger movements, and finger-on-hand positions. While previous works have examined mid-air interaction and hand gesture detection in general, there has been little investigation of in-air and finger-on-hand postures when simultaneously holding a pen.

Our main contribution in this paper is an elicitation of alternative pen-holding postures that people deem acceptable for mode-switching and command invocation. By conducting these inquiries independent from any specific sensing technology, we capture unconstrained preferences for variations of pen grip and pen manipulation. To also make our investigation concrete and applicable, we explore the possibility of using an electromyography (EMG) armband and evaluate a subset of those postures suggested by each participant, to which we add grips with mid-air and finger-on-hand positions that theoretically lend themselves to detection using muscular electrical activity. We train a deep convolutional neural network (CNN) on the EMG data transformed in the frequency domain using within and between-participant splitting schemes. Our results show that while recognition accuracy for between-participant splits is above 30% and

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50% for five and three-posture sets respectively, within-participant splitting achieves recognition above 70% and 80%.

RELATED WORK

Our work relates to interaction techniques to enhance pen input and general hand pose sensing.

Pen Interaction Enhancements

Many techniques have been proposed to minimize the need to use a conventional graphical user interface (GUI). One popular approach that has been widely explored is using touch input from the other hand [1,10,13,24,25,29,45]. The division of labour between the dominant and non-dominant hands allows the pen to mostly focus on its inking role, while the other hand performs mode-setting and assistive actions. While this interaction paradigm provides a wide range of potential enhancements to pen input, it has some shortcomings: It is mostly suitable for large surfaces such as digital tabletops and graphic tablets where both hands can freely interact on the surface, and bimanual interaction with pen and touch displays is not intuitive for most people [23]. Techniques based on how the non-dominant hand grips the tablet have also been proposed [12], but they are limited to how freely that hand can move while holding the device.

As an alternative, unimanual techniques using only the pen-writing hand are better suited to tablets and arguably more intuitive. People already use pencils to "switch modes" using the eraser end and issue "commands" like changing the colour with a button on some specialised pens. One way to achieve digital unimanual pen techniques is by adding sensing capabilities to the pen itself. For instance, tilt sensing can detect when the pen is held upright to invoke a menu [11]. With magnets, orientation on and above the surface can be detected to support further gestures [15]. A bendable stylus improves expressivity in digital art [6]. A grip sensor around the pen barrel enables detection of different grasping postures, which can be mapped to discrete or continuous actions (e.g. rubbing the index finger against the barrel) [12,33,36,37]. Most closely related to our investigation are Cami et al.'s unimanual pen-holding postures based on how the fingers and hand contact the tablet [2]. This technique requires no specialised pen sensors, but the posture set is constrained by the contact-based sensing method.

Using modified ways of holding and manipulating the pen is a compelling approach, but the postures and actions in previous works above were at least partially chosen to match technical sensing capabilities, rather than what seem natural to users. Our work begins with a study to understand what normal and alternative handwriting postures people naturally choose, without constraints from sensing hardware.

Hand and Finger Sensing

Instead of inferring hand poses with sensors embedded in the pen or tablet, the poses of the hand can also be tracked by external sensors. These sensors can be placed directly on the hand, like a data glove [19] or light motion sensor boards on the fingers [14]. However, instrumenting the hand can impede dexterity, movement, and object manipulation.

An alternative is to use sensors not mounted on the hand. The most widespread approaches use computer vision with [17,35,42] or without [28,49] depth sensing. The majority of these techniques are geared towards tracking bare hands, but some also handle hands manipulating objects [9,34]. Vision-based systems have become more accurate and robust with the increased resolution of cameras and the advent of deep learning, but they also have some limitations. For example, they have restricted tracking range (limited to the instrumented area) and reduced detection accuracy in the presence of occlusions. Alternative mobile solutions consider locating the sensors not directly on the hand, but on the arm. Here again, accelerometers [40,43] or cameras [18] can be used for coarse hand gesture or limited-range pose detection, but for more precise estimation, on-body sensors that can read low-level signals of anatomical features and activity seem quite promising. For example, pressure (force) [5], electrical impedance tomography [47], ultrasound [16,27], infrared [26], and electromyography (EMG) [31,46].

We are not aware of works that attempt to recognise pen-holding postures using external sensors that can capture finger positions when not touching the pen or the tablet. For instance, extending the pinkie in mid-air cannot be detected by a grip sensor on the pen [12,33] or the touch sensor on the tablet [2]. Based on the results of our study, we evaluate how well a consumer EMG armband recognises some of these postures. EMG has already been previously used to detect written digits and sketches [22,44], so it seems like a reasonable approach for detecting different pen grips.

STUDY

We conduct a two-part study to elicit and evaluate different pen-holding postures for general tablet input, including mode-switching and command invocation. The intention is to gain an understanding of feasible grip variations, considering people's preferences and capabilities. Note this is not a classic "elicitation study" [38,41], since we are not interested in mapping specific postures to individual commands (our study does not use different "referents"). We use the term "elicit" in the broader sense, to draw out natural pen grip postures from participants that could be used for general pen input, without associating specific actions to them.

Our study has four goals: discover user-proposed pen-holding postures suitable as interaction techniques; measure subjective preference for the participant's top proposed postures and a set of pre-selected postures (chosen for representative diversity and suitability for EMG sensing); formulate design guidelines for grip-based pen interaction based on the results; and gather data to assess the practicality of posture detection using a commercial EMG armband.

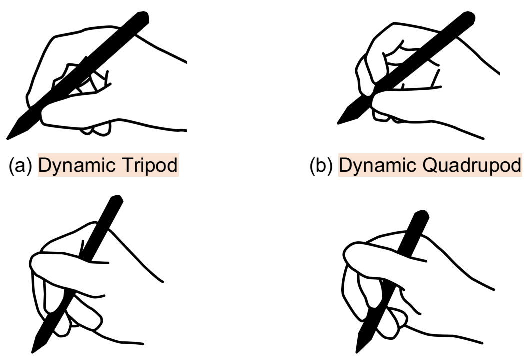
Participants

We recruited 30 volunteers, 10 female, 20 male, with mean age 34.6 (SD=7.9). 4 were left-handed and 24 right-handed.

Two participants declared themselves ambidextrous stating that they used their right hand to write and their left hand to draw. We only allowed the tasks to be carried out with the same hand and both chose to perform the experiments with their right hand. 6 participants were frequent users of pen-operated devices (daily or weekly use), 10 occasionally used digital pens (once or twice a year, typically to digitally sign) and all others never used digital pens. With regard to potential wrist or hand motor impairments, only one person declared minor reduced wrist extension range due to an operation. This did not impede their handwriting ability in any way. One participant's arm was too thin for the EMG armband, so we did not record any EMG data for them, only their subjective scores and feedback.

Part 1: Posture Elicitation

In the first part of the study, participants propose different pen holding postures that would still allow them to write or draw, without consideration for current or future sensor technologies. Our criterion for "different" is poses that can be recognised as such by a human observer or by a low-level body signal sensor such as EMG or ultrasound.



(a) Dynamic Tripod (b) Dynamic Quadrupod

(c) Lateral Tripod (d) Lateral Quadrupod

Figure 1. Common handwriting posture styles (called "mature pen grasps" in occupational therapy literature) [32]

We also observed the normal handwriting posture (or postures) of each participant. Surveys from the occupational therapy literature identify four "mature pen grasps" [7]. By far, the most common is the *Dynamic Tripod* [32] followed by the *Dynamic Quadrupod,* with a less common variation for each: *Lateral Tripod* and *Lateral Quadrupod* (see Figure 1). People may further change their grip depending on the type of pen task (handwriting, drawing, shading, etc.). We expect even more variability when people propose even less conventional pen-holding poses, but we hope that a set of relatively popular candidates will emerge.

Protocol

Participants sat or stood at a height-adjustable desk with a Wacom Cintiq 22HD Touch and stylus as well as a piece of paper with a ballpoint pen. They were asked to adjust their seat and the height of the desk to their liking. The concept of mode-switching was explained using the selection of various stroke styles and pen functions in the menus and toolbar of Microsoft Paint. This was used as motivation for using different pen-holding postures for more efficient mode-switching. Participants were then asked to find at least three ways to hold or manipulate a pen for handwriting and sketching that differed sufficiently from their normal handwriting pose. They were also told that those postures should be easily achievable from their normal pen grip and were only intended for momentary switches, such as temporarily changing to an eraser. The experimenter did not demonstrate any examples of alternative pen grips to avoid introducing any bias. The participant was encouraged to try their proposed postures with the stylus on the tablet, and with the ballpoint pen on paper. Once they exhausted possible postures to propose, they were asked to choose three of their suggested postures they felt were most comfortable and controllable. These formed their elicited posture set to be tested in part 2.

Part 2: Performance and Preference

In the second part, we use Cami et al.'s protocol [2], where participants perform a variety of pen tasks using different postures, rating each for comfort. During these tasks, participants wore a Myo armband (Figure 2) to record EMG data in order to later test recognition using machine learning.

Figure 2. Participants wore a Myo armband to capture EMG data while performing pen tasks on the tablet.

Postures

In addition to the participant's normal handwriting posture and their three elicited pen-holding postures from part 1, they also tested a set of 7 pre-selected pen-holding postures representing different types of poses from previous work and new postures not tested before (6 of these are illustrated in "Pre-Selected Postures" in Figure 3):

- The two highest rated postures from Cami et al. [2]: contacting the side of the palm on the surface (*Side Palm*) and keeping the entire hand off of the surface (*Floating Palm*).
- Two new postures with one finger extended in mid-air away from the pen: *Extended Index* and *Extended Pinkie*.
- Two new pressure-based postures that we hypothesised would be detectable using EMG signals: *Grip Pen Firmly* and pressing the pinkie and ring finger against the palm (*Press Ring and Index Against Palm*).
- In addition, we included the lowest rated posture from Cami et al.'s set of potential postures: simultaneously contacting the tablet with the side of the palm and all fingers

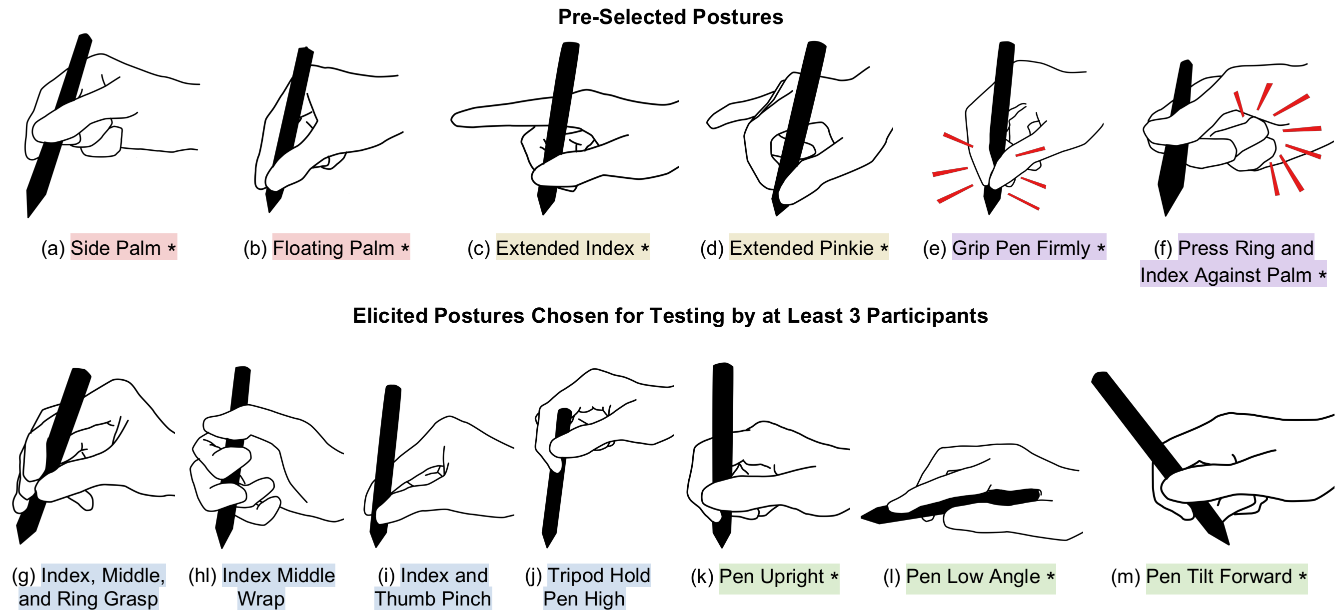


Figure 3. Pre-selected postures tested by all participants (a-f) and postures chosen by at least three different participants for inclusion in part 2 of the study (g-m). Variations of normal postures are marked with * (these postures do not specify the exact way the hand is holding the pen, which is dependent on the participant's normal pen grip). Colours denote different categories of postures: fingers gripping the pen (blue), pen tilt (green), tablet contact (red), extended finger (yellow), pressure on the pen or hand (purple).

while holding the pen (STIMRP using their notation). This forms a theoretical lower bound.

In sum, the number of tested postures for each participant was: 1 normal + 3 elicited + 7 pre-selected = 11 postures. When a participant's elicited posture coincided with a pre-selected posture, it was only included once.

Protocol

Before beginning a set of tasks with a specific posture, the participant practised by writing and tracing on an empty tablet screen. No EMG data was recorded during this practice. Then, the participant performed 15 different pen input tasks with the posture. The tasks were identical to that of Cami et al.: 13 *constrained* tasks (tracing, shape drawing, crossing, and tapping), and 2 *unconstrained* tasks (freeform sketching and writing). The order of tasks was randomised within these constrained and unconstrained groups. After performing all tasks using a specific posture, the participant rated it on a continuous scale from 1 (best) to 7 (worst) with a step of 0.5. They were told to consider both comfort and controllability. Each rating was input using a horizontal slider on the tablet, and all ratings up to the current posture were displayed as a list so the participant could adjust previous scores to make their rating more relative than absolute.

Participants performed the first two runs of tasks with their normal grip and the STIMRP posture, i.e. the best and likely the worst postures, in order to experience the two extreme conditions first. The order of the remaining postures was randomised. Participants were told they could take breaks at the end of any run if they wished. After they completed all tasks for all postures, the experimenter conducted an interview to gather detailed feedback. At the end of the interview, participants were offered a choice of snacks as a thank-you. On average, each participant took 45 minutes to complete both parts of the experiment.

Results

Most participants needed time to think and experiment to propose viable alternative postures. Some already used multiple postures to write and draw. For example, two participants had learned traditional calligraphy in school, so they proposed postures matching brush-holding grips they had been taught. Overall, participants proposed 123 postures, which corresponds to an average of 4.1 postures per participant. Within the 123 individual postures, only 7 matched those in the pre-selected posture set. 2 were identified as *Extended Index*, 3 as *Extended Pinkie* and 2 as *Floating Palm*.

Normal Handwriting Posture	Number of Participants
Dynamic Tripod	25
Dynamic Quadrupod	2
Lateral Tripod	1
Lateral Quadrupod	1
Index Middle and Ring Grasp	1

Table 1. Normal handwriting postures used by participants

Normal Pen-Holding Postures

Most participants adopted the *Dynamic Tripod* as a normal handwriting posture, while the rest used other mature grasps with one participant using a normal posture we later identify as *Index Middle and Ring Grasp* (Table 1).

Unique Elicited Postures

To identify unique elicited postures among individually proposed poses, we used these key features: number of fingers touching the pen, whether the fingertip or finger pad is used, the position of the grip along the pen barrel relative to the nib (low, normal, high), pen tilt angle (low towards the user, normal, upright, forward tilt), and the amount of wrist and arm rotation relative to a normal grip (normal, curled). This process yielded 53 unique postures: Figure 3g-m illustrates 7 common examples proposed by at least three participants for inclusion in part 2 of their session. Notably, almost all proposed postures used finger, hand, or forearm position, or pen angle. No one suggested pressure-based postures, and only two participants suggested postures with fingers contacting the tablet, but these were to help support the hand.

Posture Types

We divide all postures into categories representing their type (shown in different colours in Figure 1, Figure 3 and Figure 4): postures that are mature handwriting grasps (peach); postures that are primarily defined by how the fingers grip the pen barrel (blue); postures that primarily use the pen tilt angle (green); postures that are identified by how the hand or fingers contact (or do not contact) the tablet (red); postures that feature a finger extended in mid-air (yellow); and postures that are defined by the pressure fingers exert on the pen or hand (purple).

Grip-Specific Postures and Variation Postures

As a further classification, we distinguish between *grip-specific postures* and *variation postures*. Grip-specific postures are those which are defined by the number and manner in which fingers grip the pen (e.g. the mature pen grasps shown in Figure 1 are examples of grip-specific postures). Variation postures are extensions of a user's normal handwriting posture that differs by criteria other than how the pen is gripped, such as pen angle, finger pressure, and positions of fingers not touching the pen. When participants only demonstrated such grip-independent aspects as defining features for their proposed posture, we classified it as a variation posture. When a participant's posture specified finger grip positions within these variations, like gripping the pen higher with tripod or quadrupod grasps, that posture was considered grip-specific. Note that variation postures can be made grip specific if the normal handwriting grip is fixed to a certain posture like *Dynamic Tripod*. We do this later when creating posture sets to evaluate EMG classification performance.

Posture Ratings

Figure 4 shows participant ratings for each of the pre-selected postures as well as normal or elicited postures from at least three participants (i.e. postures rated by at least three participants). We do not formally rank and statistically compare posture ratings since the number of samples differs greatly. Our goal is to present an overview to make general recommendations rather than empirically argue for superiority of certain postures over others.

Unsurprisingly, postures that are mature grasps obtained excellent ratings (peach bars in the figure). The remaining postures received diverse ratings with wide score ranges, suggesting no consistent preference across participants, but some general trends can be observed.

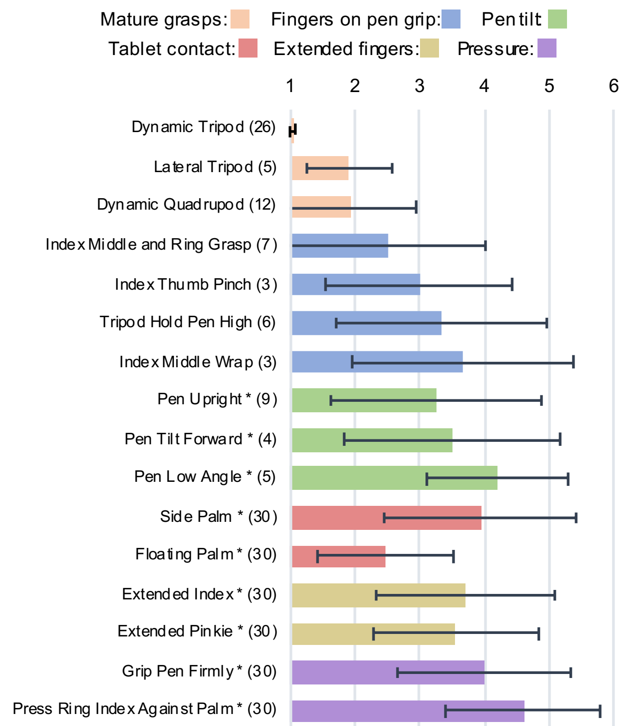


Figure 4. Subjective posture ratings from 1=best to 7=worst (scale in graph from 0 for better visibility). Numbers in parenthesis are number of ratings. Error bars are std dev.

Pressure-based postures seem to be the most disliked as they required maintaining pressure throughout the task (purple bars in the figure). Several participants said this was fatiguing and felt they were less comfortable than other postures. However, during the interview, all those participants suggested pressure would be suitable for short-time use, such as briefly squeezing the pen to invoke a menu.

Perhaps the next best group of postures are those using different ways for the finger and hand to grip the pen (blue bars in the figure). Simply placing more fingers on the barrel, as with *Index Middle and Ring Grasp*, seems to be largely acceptable as the stability of the pen is maintained. Conversely, *Index Thumb Pinch* afforded less control with two fingers, and so was less preferred. Wrapping fingers around the pen, or gripping it higher, was even less favoured due to decreased precision. Two participants, however, mentioned that *Tripod Hold Pen High*, provided better screen visibility as the hand was not as much "in the way".

Among the postures involving different orientations of the pen (green bar in figure), *Pen Upright* seems to be moderately acceptable, while *Pen Low Angle*, used by artists for shading and on vertical drawing surfaces, was deemed less suitable for writing and sketching. *Pen Tilt Forward* also received intermediate ratings, but like *Tripod Hold Pen High*, it also creates less hand occlusion.

Regarding the postures based on how the tablet surface is contacted with the fingers or hand (red bar in figure), *Side Palm*, which scored very highly in Cami et al.'s evaluation [2], was not as well received by participants, mainly due to friction when dragging on the display (9 participants), but also because of the requirement not to touch the screen with the pinkie (2 participants). Two participants deemed the posture suitable for local input, i.e. when pen input is concentrated in a small region and the hand does not need to move much, thus minimising friction. *Floating Palm*, on the other hand, did not suffer from such problems leading to better ratings, although three participants commented that this posture was fatiguing. Two participants stated that it was close enough to their normal handwriting posture, but two other participants said that the "floating" aspect reduced stability and precision. We also observed that roughly a third of our participants kept their arm raised when performing tasks with most postures, so *Floating Palm* may not have felt any different. This inclination to keep the palm raised above the tablet in most cases suggests it may not be reliable as a distinct input posture. Interestingly, this behaviour is specific to the tablet and when using a normal pen on a piece of paper, participants naturally rested their hand. Even though people were explicitly told that touch had no effect on the tablet, it seems they were influenced by long-standing habits of using touchscreens, where unintentional touches can lead to undesired consequences.

Finally, postures with extended fingers into mid-air had mixed results. Four participants said it was generally difficult for them to straighten a finger while writing, and two who used the *Dynamic Tripod* as their normal posture, said that extending the index finger made their grip unstable. As with the pressure-based postures, however, the difficulty is mainly in maintaining the pose rather than forming it and three participants, who rated finger extensions negatively, agreed that these postures would be fine for short-time use. Extending the index finger was much a less of a problem for *Dynamic Quadrupod* users, since three other fingers remained to grip the pen. This shows that feasible postures to some extent depend on an individual's normal handwriting grip.

DESIGN GUIDELINES

We examine how these results can be used to inform the design of posture-based pen interactions. As noted above, beyond the tripod and quadrupod mature grasp postures which are broadly liked and adopted, there is a wide variety of grips for which preferences are not unanimous. These preferences can further depend on several contextual factors associated with the type of pen task, such as precision requirements, whether occlusion is important or not, if and how long the posture should be maintained and the degree of friction of the screen surface. While it was not possible to cover all these aspects in our experiments, we believe we can identify some key design guidelines for grip-based pen interaction.

First, designers should decide if they want to design for grip-specific postures or variation postures. Considering the favourable ratings for the mature grasps, if the sensing environment supports it, we recommend designing for grip-specific postures. This allows people with *Dynamic Tripod* as normal posture to use *Dynamic Quadrupod* as an additional posture and vice versa. Furthermore, it makes the posture sets clear and unambiguous so that a large number of well differentiated grips can be included. Caution is required for normal postures, however, as some people tend to vary their grip during pen tasks. Some of our participants indeed indicated that they occasionally hold the pen at different angles, slightly extend their pinkie, or support their hand by placing other fingers on the tablet when writing and drawing. Importantly, they do that unconsciously, meaning that the chance of false positives would be a concern if a mode or command posture relies on those characteristics for detection.

If designing for variation postures, even more care is needed to avoid characteristics that overlap with the user's normal grip. Due to the variety of normal pen-holding postures, alternative poses would have to be sufficiently different to avoid misrecognitions. In those cases, a good strategy may be to first require users to register their normal grip(s). Based on the grip pattern of those normal postures, the system could then suggest different additional poses to use for modes or commands.

Regarding the general applicability of the different categories of postures, we need to distinguish between poses suitable for maintained modes (quasimodes) [30] that are both comfortable and cause little fatigue, and postures that are only appropriate for momentary triggers such as mode switches and commands like invoking a menu. For maintained modes, we believe using mature grasps (Figure 1) and their variations which have at least three fingers on the pen to keep it stable, are good candidates. Fingers can be added to and removed from the pen barrel to create different touch patterns. In this sense, the pen might be considered like a flute, with different combinations of finger placement associated with different modes.

For momentary trigger postures, poses using pressure ("quick squeeze"), finger extensions ("air clicks"), pen tilt ("flips"), and tablet touches ("taps") are reasonable options, with some caveats. For finger extension, since preferences and motor skills differ among people, it is safer to allow any finger to be extended without specifying which one. For postures involving tablet contacts, like those proposed by Cami et al. [2], there might be issues for people with long nails, as was the case for two of our participants. Finally, *Floating Palm* is only practical if it is used with other postures featuring tablet contacts. In the general case, too many people use tablets without resting their arms for it to be recommended.

Sensing requirements

The above recommendations assume that the postures can be reliably detected and differentiated by whatever sensors are available. Of course, the choice of postures may be heavily influenced by the sensing environment and its actual detection performance. Many of those postures can be detected by a grip sensor on the pen, but reliably differentiating them might be a challenge, considering their variability among users. Song et al. note that the recognition of their wrap grip was problematic even for the same user [33]. Although, their Naive Bayes classification approach can no doubt be improved upon by using modern deep learning techniques. The main technological downside of a grip sensor integrated in the pen is that it needs to be powered and contain a transmitter. In contrast, postures based on tablet touch and pen tilt detection can be supported without significant pen instrumentation, increasing their practical appeal. As for body sensors such as EMG, they require equipment to be worn, reducing their current practical deployment. However, the sensor form factor could be made unobtrusive and more convenient with future EMG-sensing wearable devices like smart watches or even smart clothing.

Limitations

Except for people who have learned to use multiple pen or brush-holding poses at a young age, the exercise of proposing alternative pen-holding postures is not easy. We also did not ask our participants to consider specific sensing capabilities and we would not expect most participants to be able to consider this technical aspect anyway. This is why we also included pre-selected postures in the part 2 tests: We anticipated that grips using pressure and touching the tablet were unlikely to be suggested. The limited time to experiment with newly proposed postures also means that it was hard for people to gauge their feasibility during prolonged use and in a wider variety of contexts. In fact, 5 participants realised through the test tasks that some of their proposed postures were not as comfortable as they originally expected. Overall, 14 participants rated at least one posture they proposed more than 1 point worse than a pre-selected grip. This even holds true when *Floating Palm* and *Side Palm* are excluded, which can be considered closest to a normal posture. Nevertheless, we believe that collectively our investigation revealed relevant issues that designers should consider for posture-based pen interaction.

There are no doubt other postures and tasks that could have been considered and investigated, but we had to keep the length of our testing session and the scale of our experiments reasonable. Despite these limitations, we believe we identified the main categories of postures as well as their advantages and disadvantages in terms of ratings informed by pen control and interaction comfort. Future work can explore more variations of promising types of postures and examine their suitability for different kinds of pen tasks.

Another aspect that we do not address, and one that is critical for efficient mode-switching, is quantitative switching costs. Some forms of pen mode switching performance have been investigated [21], but not for different pen-holding postures. It is not clear how easily and quickly people can change from one pen grip to another. For instance, we surmise that holding the pen higher, while potentially comfortable, incurs a heavy switching cost. Future work should examine these performance aspects and to what extent selected postures can be used for short (mode) and longer/maintained (quasimode) switches.

DETECTION WITH EMG ARMBAND

We now turn to classifying main postures from the study using the data collected from the EMG armband. Deep neural networks are trained to classify different subsets of postures with results reported within and between participants.

Data Sampling

To provide a good user experience, the posture should be classified as soon as possible on, or shortly after, each pen-down event. For our experiments, we chose to limit the maximum latency to 100ms, which, even after adding data transmission and processing time (~40ms), is an acceptable delay to retain a responsive user interface [4].

Since the user forms the desired posture before the pen-down event, the classifier can make use of the sensor data immediately before and after the event. Choosing a reasonable value for this window length is a trade-off between computation time and accuracy [2]. We chose to use a window that captures 1 second of data prior to pen-down, and 60ms of data immediately after. This creates a total sensor data window length of 1060ms. Note that since it is the pen-down event that triggers a user-perceivable action to be taken based on the posture, it is only the 60ms of sensor data immediately following the pen-down event that contributes to the latency. Since the Myo device has a sampling rate of 250 Hz, this corresponds to $1060 \times 250 = 266$ samples. This window of 266 samples $\times$ 8 electrodes = 2128 raw sensor values constitutes our data input unit to compute a spectrogram in a pre-processing step.

Spectrogram Pre-processing

Spectrograms, also known as magnitude short-time Fourier transforms (magnitude STFT), convert time-domain waveforms into time-frequency images. Such a time-frequency image can then be used for visualising the change in frequency content of a signal over time. Spectrogram features have been shown to work well for EMG-based gesture recognition [3], so we convert the raw input data of our sampling window into a spectrogram.

Computation of the spectrogram involves choosing two key hyperparameters: the fast Fourier transform (FFT) size, and the hop size. The FFT size, which is typically chosen to be a power of 2 for efficiency reasons, determines the trade-off between resolution in the frequency domain and in the time domain. It needs to be chosen large enough to resolve the frequencies of interest but will also reduce resolution in time as it is increased. The hop size parameter specifies the number of samples to advance before computing another FFT. It determines the amount of overlap between successive FFTs. We chose an FFT size of 64 samples (256ms) using the standard Hann window and a hop size of 8 samples (32ms). This results in the spectrogram having 33 frequency bins and 26 time slices (adding up to the 1060ms of our input window). We compute this spectrogram for each of the 8 EMG sensors, resulting in a 3-dimensional array of size 33 × 26 × 8 (frequency bin × time index × sensor index).

The resulting spectrograms are globally scaled such that all values are in the range [0, 1], normalising by the maximum value observed over all training participants. We found this to perform considerably better than scaling by the maximum value of each spectrogram individually.

CNN Classifier

Given the dimensions of our input, we can consider several possible neural network architectures to use as the classifier. In an attempt to avoid using an unnecessarily complex architecture, we initially experimented with a simple neural network with three fully-connected layers. Such an architecture with three invariant dimensions would be a reasonable choice given no knowledge of spatial structure in the input spectrogram features. However, given the nature of EMG signals, it would be desirable to have some invariance to small shifts along the time axis, as well as invariance to rotation of the Myo device around the arm, which corresponds to invariance to shifts along the EMG sensor axis. We can achieve the desired shift invariances by making use of an existing CNN architecture originally designed for image recognition tasks if we format our spectrogram features so that the "image" height and width dimensions correspond to the spectrogram "time index" and "sensor index" dimensions, respectively. We then place the spectrogram frequency dimension along the channel dimension (which would correspond to the RGB colour channel in the image domain). Since the resulting spectrogram "image" resolution is quite low (26 × 8), a shallow network should be sufficient, so we use a CNN with two convolutional layers. We empirically observed such a CNN architecture to perform better than the fully-connected architecture, and so we use a CNN in our experiments.

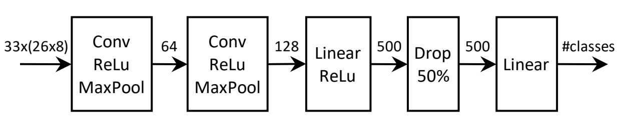


Figure 5. CNN architecture

The resulting CNN architecture, shown in Figure 5, consists of two convolutional layers and two fully-connected layers. Each of the convolutional layers has a kernel size of 3×3 and is followed by a ReLU activation and a max-pooling layer with a kernel size of 2 and a stride of 2 that serves to reduce the resolution by a factor of 2. The first convolutional layer has 64 channels and the second layer has 128 channels. The first fully-connected layer has 500 output units and is followed by a ReLu activation and uses dropout with probability 50%. The final fully-connected layer is followed by a softmax function with the usual cross-entropy classification loss. We use the Adam optimiser [20] with 'alpha' parameter value of $3e^{-4}$. We train with a mini-batch size of 50.

Model Training and Evaluation

Dataset splitting

Since our participants maintained the same posture throughout each task, we can use all available data when constructing the training datasets. Specifically, we collect a 1060ms window of sensor data, advance the start index such that 75% overlap between the next window occurs, collect another 1060ms of sensor data, repeating until we reach the end of the data sequence. This results in several partially overlapping windows of sensor data that we found improved validation accuracy. Validation and testing, on the other hand, need to reflect when postures are detected in real applications on pen down, so we validate and test only on those events.

Evaluation Types

We perform two types of evaluation: *within-participant* and *between-participant*, reflecting situations where data of a new user is included or not when training the classifier. For within-participant, this amounts to a new user having to perform a calibration step to record user-specific data for training the model including that data or to fine-tune a pre-trained model (transfer learning). This generally results in increased recognition accuracy for the user. With between-participant, a pre-trained network is used *as is*, so a new user can immediately use the interaction technique without calibration, but at the cost of decreased recognition performance.

For our within-participant evaluation, we split the data of all participants according to task type (recall that our experiments consist of tracing, tapping, sketching, and writing tasks). Specifically, we train on the tracing task data, validate on the sketching task data, and test on the writing and tapping task data. The tracing tasks generate the largest amount of data which makes them ideal for training. Sketching, writing, and tapping are more representative of real-world tasks that could leverage mode-switching or command invocation input using pen-holding postures. All task types are however sufficiently similar that the data of one task is useful for the other types. Our chosen separation is simply to avoid purely random splits over all tasks, which would have less ecological validity. The training set consists of all EMG data captured throughout the associated tasks, but the validation and test sets only contain data in the time window around pen down to reflect when a mode-switch or menu would be triggered in applications.

Our between-participant evaluation tests the ability of the classifier to generalise to participants for whom no training data is available. To achieve this, we train the model on 17 randomly chosen participants (~57% of the total data set), validate on 6 other participants (~21%), and test on the remaining 6 participants (~21%). Here again, we train on all available data, but validate and test only on pen down events. Due to the relatively small number of participants, we choose

Grip-Specific Postures	Within (train/valid/test)	Between (train/valid/test)
Dynamic Tripod, Ring and Index Against Palm, Grip Pen Firmly, Extended Index, Extended Pinkie	73.0% (19379/922/2938)	32.4% (22299/973/1571)
Dynamic Tripod, Ring and Index Against Palm, Extended Pinkie	85.7% (11763/552/1766)	53.1% (13532/591/951)
Dynamic Tripod, Ring and Index Against Palm, Grip Pen Firmly	78.9% (11672/564/1763)	56.3% (13371/587/946)
Dynamic Tripod, Ring and Index Against Palm	88.5% (7857/375/1181)	67.1% (9012/398/638)
Dynamic Tripod Extended Pinkie	89.3% (8823/407/1291)	68.0% (9458/571/692)
Dynamic Tripod, Dynamic Quadrupod, Index Middle and Ring Grasp	80.7% (7248/335/1041)	
Dynamic Tripod, Dynamic Quadrupod	84.3% (6316/292/908)	

Variation Postures	Within (train/valid/test)	Between (train/valid/test)
Normal, Ring and Index Against Palm, Grip Pen Firmly, Extended Index, Extended Pinkie	70.3% (26084/1226/3859)	33.2% (25926/2143/2055)
Normal, Ring and Index Against Palm, Extended Pinkie	83.7% (16833/779/2459)	50.8% (16656/1388/1325)
Normal, Ring and Index Against Palm, Grip Pen Firmly	80.2% (16762/793/2468)	58.4% (16474/1396/1318)
Normal, Ring and Index Against Palm	89.2% (12129/564/1769)	70.5% (11862/1022/951)
Normal, Extended Pinkie	86.8% (12075/551/1736)	64.7% (11758/1004/940)

Table 2. Within and between participant classification results for grip-specific and variation postures. Top grey rows show the results of postures using data from participants using only *Dynamic Tripod* as their normal posture (left) and the corresponding results for normal postures and their variations including all participant data (right). Bottom two green rows are for within-participant sets of grip-specific postures irrespective of the normal posture used.

5 random participant splits and average the resulting accuracies on the test set to calculate the final value.

Posture Selection

We consider two types of train, validate, and test sets focusing on grip-specific postures and variations of normal postures (grip-specific and variation postures are described earlier). For sets focused on variation postures, we take the participants' normal handwriting posture (denoted as *Normal*) and variation postures from the pre-selected set of part 2 of the study. For sets focused on grip-specific postures, we could simply select only grip-specific poses, but this would limit comparisons given there are fewer examples (see lower counts for grip-specific postures in Figure 4). Instead, we only include participants who use *Dynamic Tripod* as their normal handwriting posture since it is by far the most common, and consider all postures from the pre-selected set to be grip-specific in this case, since they are all variations of *Dynamic Tripod*.

We evaluate different combinations of postures for which sufficient amount of data is available (more than 25 participants). We do not include postures that can be easily detected by the tablet's sensors such as touch contact and pen tilt angle. We are mostly interested in recognising postures based on finger grips on the pen, extended fingers and pressure (peach, blue, yellow and purple categories in the figures above). A comparison with large amounts of data and minimal imbalance between the postures therefore mostly limits the posture sets to five postures or less from Figure 4: *Normal* or *Dynamic Tripod*, *Ring and Index Against Palm*, *Grip Pen Firmly*, *Extended Index* and *Extended Pinkie*.

Classification Results

Table 2 shows classification accuracy for a variety of combinations with the different evaluation types. In addition to direct comparisons between grip-specific posture sets for *Dynamic Tripod* users and their variation equivalents, we provide results (at the bottom left of the table) for two sets that include *Dynamic Tripod* and other popular postures with less data.

In within-participant evaluations, accuracy is above 70% for 5-posture sets, and above 78% for groups of 3 and 2 postures. There is a notable difference when looking at between-participant results. Classification accuracy is only slightly above 30% for 5 postures, above 50% for 3 postures, and between 64 and 71% for 2 postures. This shows that the models are heavily user-dependent, especially for sets with more than two postures. With the Myo, a per-user calibration is almost essential (matching how the commercial Myo software also requires per-user calibration for mid-air gesture recognition). A set of three popular postures (for which switching seems relatively easy), *Dynamic Tripod*, *Dynamic Quadrupod*, and *Index Middle and Ring Grasp*, have a within-participant classification accuracy slightly above 80%. This may be sufficiently practical if the recognition algorithm also includes temporal consistency-checking measures, such as voting schemes across successive EMG frames.

The differences between grip-specific and variation postures are fairly small. This is most likely because the overwhelming majority of participants used *Dynamic Tripod* as their normal pen-holding grip, so there is not enough data to mitigate its overall influence on the model. More data from participants using other postures would be required to reduce that bias.

Sensor Limitations

The results show that the Myo armband can recognise only a limited number of pen-holding postures. This EMG device is not sufficiently precise to reliably discern fine finger movements within the noisy activity of writing and sketching, especially for unknown users. However, we do not believe that this is a weakness of electromyography per se. The Myo was designed more than 6 years ago and is now discontinued.

Future EMG sensors, like the CTRL-labs wristband, might have the required sensitivity to enable full hand and finger pose estimation in pen tasks [50]. There are also other types of body activity sensors that might be suitable [16,26,27,47] and time will tell which sensing technology will prevail. We imagine future wrist-worn devices with high-precision embedded body sensors that will significantly enhance pen, touch, and gestural interaction in general through hand pose reconstruction.

CONCLUSION

We have presented a formative study using 30 participants that investigated alternative pen-holding postures for pen interfaces utilising pen grip for modes or action triggers. Subjective preference ratings of postures elicited from participants and pre-selected poses informed a set of design guidelines for such interfaces. Specifically, we believe that the four main normal postures (mature grasps) and variations thereof where additional fingers grip the pen are suitable for maintained modes (quasimodes), whereas postures based on pressure, finger extensions, pen tilts and tablet contacts should only be used for quick mode switches. We further gathered EMG data via a commercial armband worn by participants to attempt to recognise those posture using a deep learning model, but we obtained mixed results. For a 3-posture subset, mean classification accuracy was above 80% for within-participant evaluations, but only slightly above 50% when evaluating between participants. We believe this is mostly due to the quality of our sensor and that future wearable devices will be able to reliably detect subtle hand and finger motions for enriched pen interaction.

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