

Note-on-Watch: Live Scribing from Board-works to Class-notes

Snigdha Das
Indian Institute of Technology
Kharagpur, India
snigdhadas@sit.iitkgp.ac.in

Rohan Singh
National Institute of Technology
Durgapur, India
rohansingh726@gmail.com

Pradipta De
Georgia Southern University, USA
pradipta.de@gmail.com

Sandip Chakraborty
Indian Institute of Technology
Kharagpur, India
sandipc@cse.iitkgp.ac.in

Bivas Mitra
Indian Institute of Technology
Kharagpur, India
bivas@cse.iitkgp.ac.in

ABSTRACT

The COVID-19 pandemic directly impacts educational systems worldwide. Although the online mode of education is the most viable solution under this scenario, it introduces new challenges to the course instructors. Primarily in the low and middle-economy countries, the majority of instructors do not have access to touch-enabled devices like tablets to mimic board-works, from where students can generate the class-notes. Pertaining to these constraints, in this paper, we propose an online note-generation system – *Note-on-Watch*, using community-off-the-shelf smartwatches and smartphones, leveraging the rapid and huge penetration of these devices across these countries. In *Note-on-Watch*, the instructor writes a text over a vertical board while wearing the smartwatch, and the locomotive data from the smartwatch is captured over a smartphone to regenerate the text to mimic on-device writing. We implement a prototype of *Note-on-Watch* using a Moto-360 smartwatch and Android smartphone and observe that the system nicely captures English alphanumerics and words.

CCS CONCEPTS

• **Human-centered computing** → User studies; *Haptic devices*; **Human computer interaction (HCI)**.

KEYWORDS

smartwatch; smartphone; collective sensing

ACM Reference Format:

Snigdha Das, Rohan Singh, Pradipta De, Sandip Chakraborty, and Bivas Mitra. 2020. *Note-on-Watch: Live Scribing from Board-works to Class-notes*. In *22nd International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '20 Extended Abstracts)*, October 5–8, 2020, Oldenburg, Germany. ACM, New York, NY, USA, 5 pages. <https://doi.org/10.1145/3406324.3417166>

1 INTRODUCTION

Educational systems worldwide have witnessed a major paradigm shift from classroom-heavy activities to online mode as a result

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s).

MobileHCI '20 Extended Abstracts, October 5–8, 2020, Oldenburg, Germany

© 2020 Copyright held by the owner/author(s).

ACM ISBN 978-1-4503-8052-2/20/10.

<https://doi.org/10.1145/3406324.3417166>



Figure 1: Ongoing Writing on Whiteboard



Figure 2: Ongoing Writing Processing on Smartphone

of the COVID-19 pandemic¹. However, the schools and colleges in the low and middle-economy countries have possibly seen the most adverse impact of this change in the environment, where instructors are not equipped with modern teaching infrastructures, like touch-enabled devices (say, a tablet with a stylus) to mimic the board-works that can be live-streamed to the students directly. Live recording of board-works using a camera is difficult as the visual clarity of the written texts depends on the angle of the camera as well as the obstructions (like the hand of the instructor or the instructor herself) that comes in between the board and the camera. Consequently, the course instructors are left with manual transfer of course materials through document sharing in an offline mode, which severely violates the essence of a classroom teaching environment [11]. Other non-conventional approaches like speech-to-text synthesis for lecture note generation², stylus-based mobile applications or light-sensor based systems [10] to capture handwritten scribbles need specialized devices like high-end microphone, stylus, scanner pen, etc. Therefore, *can we develop a live system for scribing the classroom board-works to a digital form*

¹https://en.wikipedia.org/wiki/Impact_of_the_COVID-19_pandemic_on_education (accessed on August 13, 2020)

²<https://www.computerworld.com/article/3174150/note-to-self-stop-taking-notes.html> (accessed on August 13, 2020)

using commercial-off-the-shelf smartphones and smart handheld devices, like a smartwatch, which have witnessed a rapid penetration at the low and middle-economy countries?

Interestingly, a few works in the literature [1, 2, 4, 6] consider inertial (IMU) sensor embedded smartphones and other wearables for capturing the handwritten text. The primary advantage of these systems is that they do not need any special application-specific device like a scanner pen or a tablet with a stylus. Additionally, the size of the preprocessed-data produced by the inertial sensor is very less compared to the image files. Noting the limitations of the current state-of-arts, in this paper, we develop a light-weight system for collecting and sharing the sensory preprocessed-data when a course instructor writes over a board, and finally generating the live impression of the board-works from the inertial sensor stream. There exist multiple challenges in designing such a light-weight inertial sensor-based system. Firstly, the majority of the works [1, 2, 6] use the smartphone as a writing device, which is not a user-friendly system for the course instructors. Hung *et al.* [4] addressed the problem by attaching a smartwatch with the pen. However, for continuous writing, such a system can distract the course instructor. Secondly, the inertial sensor readings are prone to noise. Recognizing the writing only from the inertial sensor stream without using any marker is difficult, as the instructor can perform various other activities apart from writing, which are also captured by the hand-mounted sensors. For overcoming these limitations, there exist multiple learning-based solutions such as MotionHacker [9] and others [7, 8] that can recognize the writing based on the inertial sensor data; however implementing an on-device solution with complex supervised machine learning algorithms is a concern.

Considering these limitations of the existing systems, in this paper, we proposed *Note-on-Watch*, a smartwatch, and a smartphone-based solution, where the course instructor performs the board-works while wearing the smartwatch on her wrist (Figure 1). The IMU data collected from the smartwatch is captured at the smartphone to process the data and generate real-time scribble of the board-works (Figure 2). *Note-on-Watch* combines two Android applications – *WatchSense* that runs over the smartwatch to collect the IMU data continuously and *NoteScribe* that run over the smartphone to process the data to generate the real-time scribble of the writing. *NoteScribe* is an intelligent processing mechanism that estimates the locus of the pen or marker from the locus of the wrist by eliminating the captured noises due to wrist-vibrations and other external activities, and finally generates the scribble from the locus of the pen. We have tested *Note-on-Watch* using four volunteers, three males and one female, using one Moto-360 smartwatch and commercial Android-supported smartphones. The initial results are promising enough; we observe that three independent validators can validate the writings with good accuracy without having any background knowledge about how the scribbles have been generated.

2 SYSTEM DESIGN

Note-on-Watch has mainly two major parts, specifically, *WatchSense* that runs over the smartwatch to collect the data and *NoteScribe* which run over a smartphone to generate real-time scribble of the board-work from the data collected through *WatchSense*. The

overall framework of *Note-on-Watch* is shown in Figure 3. *Note-on-Watch* gets the IMU sensor data from a smartwatch and sends the generated preprocessed-data to the smartphone through a paired network connection. On the other side, the preprocessed-data is processed to generate the note over the smartphone.

2.1 WatchSense - Data Collection Component

This component logs the raw accelerometer and gyroscope data from the smartwatch and transfers the collected preprocessed-data to the connected smartphone. Both the inertial sensors – accelerometer and gyroscope provide the tri-axial data, which is stored with the time information for maintaining the synchronization between the multi-domain data. Finally, the stored data is transferred to the smartphone for standalone processing.

2.2 NoteScribe - Data Processing Component

This component is the core of *Note-on-Watch*. It solely generates the scribes by extracting the relevant data from the received preprocessed-data. First, the sensor stream is preprocessed to identify the writing segment. Next, we calibrate the gyroscope data using the accelerometer data stream. Finally, we estimate the locus of the writing from the calibrated data.

The segmentation module ensures that only the writing segment corresponds to the board-work is extracted from the entire sensor data stream. The motivation behind this module is to identify the starting and ending of the sensor signal corresponding to the board-work. While writing on the vertically align board, the writer uses to give a pause on the start and the end of the writing. We utilize this natural characteristic for finding the board-work segment from the entire data stream. Specifically, we apply a sentinel-based method where the writer holds the pen on the board at a fixed position for t time unit before and after performing the board-work. Figure 4 shows a representative raw accelerometer signal of the board-work session. We find that the board-work segment with more curve signal lies in between two non-board-work segments with a comparative smooth signal.

Towards the first step of the starting and ending sentinel detection, we first smooth the raw accelerometer signal by applying a moving average of window size w . In the next step, we employ a moving variance of window size ω on the smoothed accelerometer data to determine the deviation in the signal. Figure 5 shows the processed accelerometer signal after finding the variance for board-work and non-boardwork segments. We find that the deviation in the signal corresponds to the board-work segment is higher than the non-boardwork pause segment. Finally, for selecting the board-work segment, we apply a two-phase thresholding method to the processed accelerometer signal. We consider that the minimum board-work time is t_b . Therefore, we extract the final board-work segment from the processed accelerometer signal, where the signal value is greater than ϵ for at least t_b time unit.

In the next module, we estimate the locus of the pen over the board using the locus of the wrist-worn smartwatch. Although this can be done with the gyroscope data, however, as the wrist experiences a free three-dimensional movement in comparison to the movement of the pen, which is mostly a two-dimensional in nature (over the vertical plane only, as the writer needs to move the



Figure 3: Note-on-Watch Framework

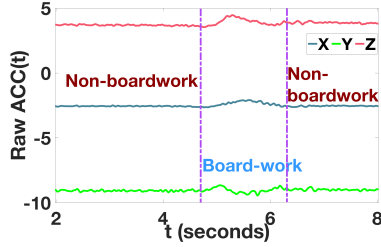


Figure 4: Raw ACC Signal Comprised of Board-work and Non-boardwork

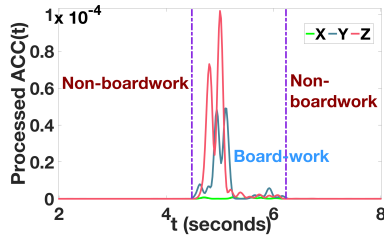


Figure 5: Processed ACC Signal Comprised of Board-work and Non-boardwork

pen on the board for writing), we get an additional *rotational drift* in the gyroscope reading. To eliminate this rotational drift, we need to fix the axis perpendicular to the vertical plane and project the three-dimensional movement of the smartwatch over the vertical



Figure 6: Starting & Stopping WatchSense Application Interface

plane only. In other words, we need to fix the reference frame for the writing-plane (which is the vertical plane) to project the gyroscope readings over that plane. For this purpose, we consider the Earth's reference frame as the *frame of reference* (FoR) and project the gyroscope reading over this FoR with the help of conventional *Euler angles*-based technique [5] as follows.

To eliminate the rotational drifts that arise due to the wrist movement, *Note-on-Watch* continuously computes the change in the orientation angle with respect to the FoR and then projects the gyroscope readings over the FoR. For estimating the smartwatch orientation with respect to the FoR, we first compute the Euler angles [5], specifically the *Roll*, *Pitch* and *Yaw* angles using accelerometer readings across the three axes. However, using a 3-axes accelerometer, we can only compute two angles by fixing the gravitational acceleration towards the Z-axis of the Earth's reference frame. Therefore, we then take the help of gyroscope readings to compute the third angle by applying the *kinematic relation* used in [3]. The kinematic relation provides the rates of Euler angles, which indicate the angular velocity with respect to the Earth's reference frame. Finally, we compute the locus of the smartwatch by calculating the angular displacement with respect to time, which gives us the locus of the pen over the vertically-placed board.

3 SYSTEM IMPLEMENTATION

We implement *Note-on-Watch* using a Moto-360 smartwatch and different models of smartphones. We use the smartwatch with *Android Wear OS 2.0* and the smartphones with *Oxygen OS 5.0.8*. In addition to the smart devices, we use a whiteboard and a marker pen for writing over the board.

3.1 Application Development

On the smartwatch, we record the data from the inertial sensors and send it to the smartphones for generating the writing scribble. Therefore, we develop two different Android-based applications – *WatchSense* and *NoteScribe* for performing the tasks in smartwatch and smartphone, respectively. *WatchSense* application mainly comprises three software components – *inertial sense listener*, *local storage manager*, and *upload manager*. The *inertial sense listener* senses the accelerometer and gyroscope with a sampling rate of 50Hz. The raw sensed data is stored temporarily in the local storage through the *local storage manager* and finally uploaded to the connected smartphone on-demand basis through the *upload manager*, which acquires negligible battery consumption. Figure 6 show the start and stop front-end view of *WatchSense*.

On the smartphone side, *NoteScribe* application has three major software components - *network manager*, *storage manager* and

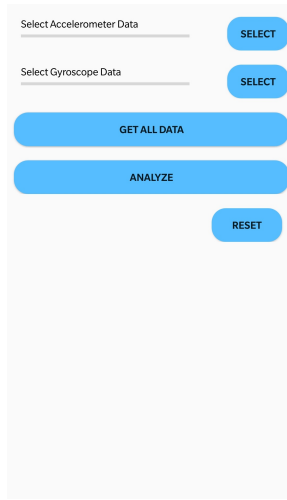


Figure 7: NoteScribe Application Interface

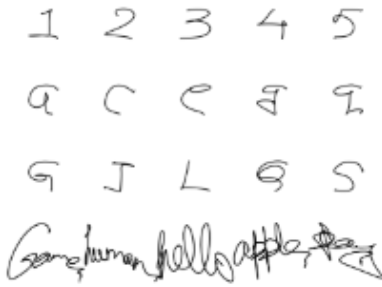


Figure 8: NoteScribe Outcome

data analysis manager. The *network manager* and *storage manager* combine to run the communication protocols to capture the data from the smartwatch and store locally the collected sensing data. Finally, *data analysis manager* processes the collected data through the python tool embedded in *NoteScribe* following the mechanism as discussed in Section *NoteScribe - Data Processing Component*. Figure 7 & 8 show the front-end view of the *NoteScribe* application and the sample output note.

3.2 Data Collection

We recruited four volunteers, including three males and one female, age between 20-35 years, to perform the board-works. Before performing the experiment, we instructed the volunteers on the writing protocol, which required to keep still his/her writing hand style posture at a fixed position on the board for two seconds (the sentinel) to denote the start and the end of writing. We consider that the minimum writing time of any character or word is one second. Each volunteer writes all English alphanumeric (26 upper case alphabet, 26 lower case alphabet, and 10 numerics) and a few words.

Table 1: Note-on-Watch Performance

User ID	Accuracy in %	All three recognized	Any two recognized	Any one recognized	No one recognized
u1	68.28	31	13	8	10
u2	61.29	27	12	9	14
u3	53.23	25	7	10	20
u4	52.15	25	7	8	22

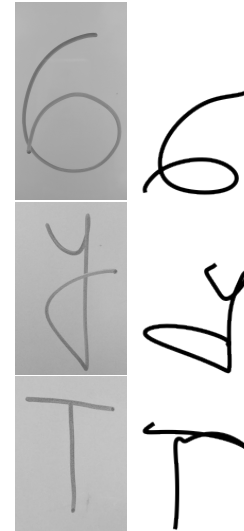


Figure 9: Comparison of Scribble of English Alphanumerics with the Ground Truth Board Written Images

4 RESULTS

For testing the decipherability of the texts scribbled through *Note-on-Watch*, we employ three other volunteers, called validators, who are completely unaware of the background process. They load the downloaded files, followed by pressing the analyse button and read the generated scribble document. The images of the writing in the whiteboard is considered as the ground truth. Figures 9 & 10 shows the system generated scribbles along with the ground truths. We observe that our system generates the characters and words, which is nearly following the same pattern with the ground truth images.

For evaluating the performance of our system, we ask the validators to identify which character is shown in the reconstruction. If he/she is not able to identify the character, it is marked as 'None'. To compute the accuracy, we compare the validators' choice with the ground truth images and mark as a correct match if the choice matches the ground truth. If the volunteer selects 'None', we count it as an incorrect match. We compute the detection accuracy based on the total number of correct and incorrect matches. Table 1 shows the performance of the system on the English alphanumeric in accuracy. We observe that the majority of the alphanumeric are recognized by all the validators and find that '0', 'F', 'i', and 'z' are the most difficult alphanumeric which are not identified by any of the validators for all users' writing. A detailed look into those scribbles, we observe that a few lower case characters (e.g: 'z', 's', 'c', 'u', 'v', 'w') are identified as the respective upper case characters

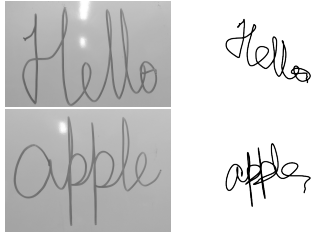


Figure 10: Comparison of Scribble of English Words with the Ground Truth Board Written Images

(e.g: ‘Z’, ‘S’, ‘C’, ‘U’, ‘V’, ‘W’) or vice versa. Some characters like (‘0’, ‘o’, ‘O’) are also recognized interchangeably. This justifies the accuracy of the system at most 68.28%. We note that although a few characters (‘l’, ‘t’, ‘p’) are not recognized in character-level, correctly identified in word-level. On the other side, a few additional lines present for the characters like ‘F’, ‘E’ that impact the readability of the generated scribbles. We plan to work with those special characters in the future.

5 CONCLUSION & FUTURE WORK

In this paper, we develop a light-weight a smartwatch and a smartphone-based system – *Note-on-Watch* for collecting and sharing the sensory preprocessed-data when a course instructor writes over the board while wearing the smartwatch on her wrist, and finally generating the live impression of the board-works from the inertial sensor stream on the smartphone. *Note-on-Watch* shows

promising results over the English alphanumeric as well as words. In the future, we plan to extend our system for sentence writing. Additionally, we want to explore our system for in-the-wild deployment for a thorough study of its performance.

REFERENCES

- [1] Sandip Agrawal, Ionut Constandache, Shravan Gaonkar, Romit Roy Choudhury, Kevin Caves, and Frank DeRuyter. 2011. Using mobile phones to write in air. In *ACM MobiSys*. 15–28.
- [2] Thomas Deselaers, Daniel Keysers, Jan Hosang, and Henry A Rowley. 2014. Gyropen: Gyroscopes for pen-input with mobile phones. *IEEE Transactions on Human-Machine Systems* 45, 2 (2014), 263–271.
- [3] Gamini Dissanayake, Salah Sukkarieh, Eduardo Nebot, and Hugh Durrant-Whyte. 2001. The aiding of a low-cost strapdown inertial measurement unit using vehicle model constraints for land vehicle applications. *IEEE transactions on robotics and automation* 17, 5 (2001), 731–747.
- [4] Michael Hung, David Ledo, and Lora Oehlberg. 2019. WatchPen: Using Cross-Device Interaction Concepts to Augment Pen-Based Interaction. In *ACM Mobile-HCI*. 1–8.
- [5] Mark Pedley. 2013. Tilt sensing using a three-axis accelerometer. *Freescale semiconductor application note* 1 (2013), 2012–2013.
- [6] Sheng Shen, He Wang, and Romit Roy Choudhury. 2016. I am a smartwatch and i can track my user’s arm. In *ACM MobiSys*. 85–96.
- [7] Hikaru Watanabe, Masahiro Mochizuki, Kazuya Murao, and Nobuhiko Nishio. 2016. A recognition method for continuous gestures with an accelerometer. In *ACM UbiComp*. 813–822.
- [8] Raveen Wijewickrama, Anindya Maiti, and Murtuza Jadliwala. 2019. deWristified: handwriting inference using wrist-based motion sensors revisited. In *WiSec*. 49–59.
- [9] Qingxin Xia, Feng Hong, Yuan Feng, and Zhongwen Guo. 2018. MotionHacker: Motion sensor based eavesdropping on handwriting via smartwatch. In *IEEE INFOCOM Workshops*. 468–473.
- [10] Chi Zhang, Josh Tabor, Jialiang Zhang, and Xinyu Zhang. 2015. Extending mobile interaction through near-field visible light sensing. In *ACM MobiCom*. 345–357.
- [11] Saijing Zheng, Pamela Wisniewski, Mary Beth Rosson, and John M Carroll. 2016. Ask the instructors: Motivations and challenges of teaching massive open online courses. In *ACM CSCW*. 206–221.