*f*Sense: Unlocking the Dimension of Force for Gestural Interactions using Smartwatch PPG Sensor

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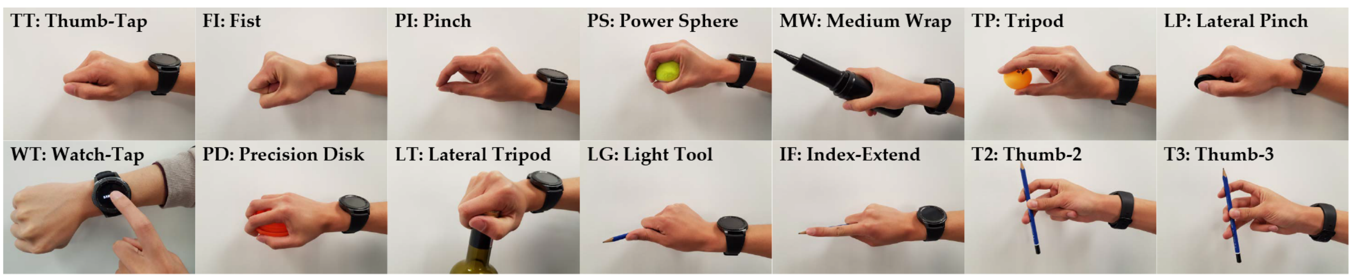

Figure 1: With *f*Sense we show that the PPG sensor of a smartwatch can be used to detect force of a grasping gesture. With the data from 12 users, we were able to differentiate between two force levels across several types of common grasping gestures.

ABSTRACT

While most existing gestural interfaces focus on the static posture or the dynamic action of the hand, few have investigated the feasibility of using the forces that are exerted while performing gestures. Using the photoplethysmogram (PPG) sensor of off-the-shelf smartwatches, we show that, it is possible to recognize the force of a gesture as an independent channel of input. Based on a user study with 12 participants, we found that users were able to reliably produce two levels of force across several types of common gestures. We demonstrate a few interaction scenarios where the force is either used as a standalone input or to complement existing input modalities.

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CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing systems and tools**; *Interactive systems and tools*;

KEYWORDS

Wearable Computing, Gesture Interaction, Mobile Sensors, PPG Sensor, Smartwatch

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1 INTRODUCTION

The way we grasp objects is incredibly rich and expressive, and we implicitly improvise from it constantly. Much of prior work focuses on detecting gestures using inertial measurement units [10], infrared sensors [7], cameras [2], EMG [8] and capacitance[11] sensors. Most of them focus on static posture or the dynamic action of the hand.

We propose a new technique using an in-built photoplethysmogram (PPG) sensor of a smartwatch to detect force as an independent input from grasping gestures. PPG is an optical sensor that measures light absorption to detect heart rate, and has been commercially-available in some smartwatches and fitness trackers. When we apply different force levels while performing different hand grasps, the tissues in our wrist contract or expand accordingly, changing the blood concentration, which is measured by the PPG sensor. With this operation principle, we hypothesized that there is a correlation between the force exerted when performing grasping gestures and readings from the PPG sensor.

Using the force of a gesture has three advantages. First, it would increase the expressiveness of hand gestural interactions, allowing the same gesture to be compounded with different force levels for various operations. Second, by mapping operations to the same gestures with different forces, we could provide an intuitive extension to the input space. Third, as an independent input modality, force-based hand input could be performed even with "busy hands", i.e., when the hand is holding onto something irrelevant to the interaction context, such as a bicycle handle while cycling, or a steering wheel while driving.

In this paper, we describe the implementation of, *f*Sense, a method to detect gesture force, using a commercially-available smartwatch. We collected and analyzed user-elicited data from 12 users and were able to differentiate between two levels of force (Soft & Hard) across several types of common gestures. We further demonstrate possible applications supported by *f*Sense.

2 RELATED WORK

Hand Grasp Recognition Techniques

Previous work on wrist-worn devices to detect gestures and objects were based on various types of signals that are detectable on the wrist using sensors such as accelerometers, gyroscopes and microphones. For example, ViBand [5] used a bio-acoustic sensing method to identify several gestures and objects which vibrate during operation, using an off-the-shelf smartwatch with an overclocked accelerometer. Serendipity [10] used an accelerometer and gyroscope of a smartwatch to detect hand gestures. On the other hand, SensIR [7] is a wrist-worn system which used IR transmitters and emitters to detect hand gestures by measuring the IR reflection on the wrist. Lastly, Tomo [15] sensed electrical impedance around the wrist to identify gestures. Most of these techniques detect dynamic gestures or static hand postures without force levels.

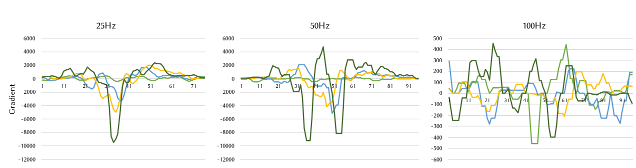

Figure 2: Gradients of the PPG reading of the *Fist* gesture, for different force levels at different sample rates

PPG-based Interaction

Since PPG is susceptible to noise from movements of the body or the limbs [6], it has been used to enable hand-based interactions. Yoshimoto et al. [13] used a PPG sensing device on the proximal part of the finger to detect change of blood flow in the finger, inferring the 3D contact force exerted on the fingertip when pressing against a surface. Zhang et al. [14] investigated the capability of a Samsung Gear 3 smartwatch to identify different types of gestures using its PPG sensor. The system could detect 10 commonly-used gestures with an accuracy of 90.55%. Zhao et al. [16] used a wrist-worn prototype with two PPG sensors to recognize fine-grained finger-level gestures. The prototype identified 9 gestures of the American sign language with an average accuracy of 88.32%. Float [9] used the PPG sensor data of an off-the-shelf smartwatch, together with an accelerometer and gyroscope data to recognize in-air finger taps with an accuracy of 97.9%. Our paper extends these works by detecting the force level with PPG in a gesture-independent way.

Sensing of Force During Interaction

Perhaps the most similar work to our project is GripSense [4], which used the gyroscope and vibration motor of smartphones to detect three levels of finger pressure on the touchscreen with 95.1% accuracy. The main difference between GripSense and our work is that it detected the force exerted specifically on the phone, whereas our work aims to detect force in an object-independent and gesture-independent way.

3 *f*SENSE

*f*Sense system was implemented using an off-the-shelf Samsung Galaxy Gear 3 Frontier smartwatch [3], which runs on the Tizen 3.0.0.1 operating system. During the pilot study we compared 3 different sample rates with the *fist* gesture, while performing three different force levels along with *No-Action*. Based on the analysis (Figure 2), we concluded that 25Hz is the most stable and less noisy sample rate to be used. To collect PPG data from the smartwatch, we created a Samsung Wear service application with Tizen version 2.3.2. Data was sent over Wi-Fi to a desktop Java application for storage and processing.

4 EVALUATION

Study

The aim of our experiment was to evaluate *f*Sense system's ability to detect different force levels of daily grasping actions. Specifically, we examined 3 user-elicited force levels: *Soft*, *Medium* and *Hard*. We also collected PPG data when the

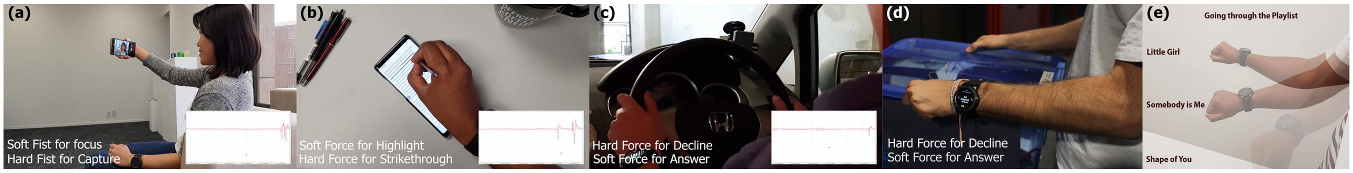

Figure 3: Example application scenarios (from left to right): a) taking "selfies", b) interactions using digital stylus, c) answering calls while driving, d) answering calls with "busy hands", and e) combined with existing motion sensors

participant was not performing any action in a static gesture position ("*No-Action*") as the baseline.

Gesture Set: 14 gestures were used in the experiment (Figure 1), 10 of them from the studies by Bullock et al. [1] and 3 gestures (*Fist*, *Pinch* and *Thumb-Tap*) from Wen et al. [10]. We added the *Watch-Tap* gesture, which is a common interaction with smartwatches. Participants were allowed to determine the duration and force level to apply for each gesture. For *Soft* and *Hard* levels, participants were required to perform gestures with the softest and hardest force they could produce respectively, while the *Medium* level is in between.

Participants: Twelve healthy, right-handed participants (7 males, 5 females) between 24 and 32 years of age (M = 28.1, SD = 2.7) took part in the study.

Procedure: Before the experiment started, participants were instructed to try out all the gestures to gain familiarity, while wearing the smartwatch on their dominant hand. Each participant performed three blocks of 56 trials each (14 gestures with 3 force levels and the *No-Action* state). The order of trials in each block was randomized. We collected a total of 168 samples (56 trials $\times$ 3 blocks) for every participant. Each trial took approximately one to two seconds to complete and, with the breaks, a session lasted around 25 minutes.

Table 1: Accuracy comparison of Logistic, Random Forest and SVM with different force level combinations (H:*Hard*, M:*Medium* and S:*Soft*)

Method	H-M-S			HM-S			H-MS		
	MLR	SVM	RF	MLR	SVM	RF	MLR	SVM	RF
Accuracy %	42.3	38.7	**46.3**	67.4	67.4	**71.7**	67.2	67	**69**
RMSE	0.4667	0.5209	**0.4571**	0.4588	0.5705	**0.4451**	0.4657	0.5746	**0.4515**

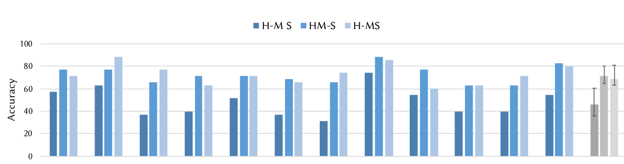

Figure 4: Accuracy for each participant using RF with different force-level combinations (H:*Hard*, M:*Medium* and S:*Soft*)

Data Analysis

Pre-Processing and Feature Extraction: By analyzing the length distribution of the data, we standardized the length per action to be 43 samples. Next, we smoothed the data with a moving average filter (window size 5), followed by calculating the gradient. The gradient time series was then used to calculate the statistics as features: mean, SD, min, max, median, skewness, kurtosis and RMS in a moving window of size 20 with 50% overlap.

Classification Algorithms: We compared three algorithms: Support Vector Machine (SVM), Multinomial Logistic Regression (MLR) and Random Forest (RF) for the classification task. We used the WEKA software [12] to test the machine learning algorithms with default parameters and 10-fold cross validation was used to test the accuracy.

Results

Force Level Classification: From the three algorithms: SVM, MLR and RF, we observed that the recognition accuracy across users was very low, most likely because all force levels were user-elicited, with large differences between users. We also combined the *Medium* force level with *Hard* or *Soft* levels to see how the accuracy varied. Based on the accuracies shown in Table 1, we selected RF as our classification algorithm for its higher accuracy and lowest root mean squared error (RMSE) compared to SVM and MLR.

Force Levels vs No-Action: An important requirement of *f*Sense is the ability to recognize between specific force levels and *No-Action*. For that analysis, we used 42 randomized data samples from the three force level data, and 42 samples of *No-Action* data from each user and the accuracy of RF was 92.1% for all users combined.

Per-User Classification: Per-user training resulted in higher accuracy as shown in Figure 4. The key observation from this analysis is that the *Medium* force level is not easily distinguishable. This could be due to the user-elicited *Medium* force level being too similar to either *Soft* or *Hard* for different users. The maximum number of force levels that can be reliably classified were two (*Soft* and *Hard* levels), except for the *Medium* level.

5 APPLICATION SCENARIOS

Object Grasping-Based Interactions: *f*Sense system would be beneficial when used in combination with objects and devices in daily life. One scenario is in taking "selfies". One hand would hold the smartphone, while the other hand, with the smartwatch attached, would perform a soft *Thumb-Tap* to take the picture (Figure 3a). This avoids having to reach for the on-screen "capture" button with a finger and renders the shutter timer obsolete. Another scenario is to use force as a mode switch for a digital stylus (Figure 3b). When proof-reading or editing a digital document, a soft grasp of the stylus, while selecting words in the document, would highlight those words. A hard grasp would strikeout the words instead.

Quick Response Interactions: Our system could be used to enable quick responses to incoming calls or notifications, independent of the object the user is holding (i.e., with a "busy" hand) or if the user is not holding anything at all. An example would be: a user could reject or answer a call while driving or holding groceries in both hands (Figure 3c, d). A soft squeeze to answer and a hard squeeze to reject. Alternatively, the user could scroll through options for auto-replies using soft squeezes, and select the option with a hard squeeze.

Combination with Existing Gestural Interactions: *f*Sense could be combined with existing gestural interactions, especially when using inertial sensors (accelerometers and gyroscopes) which are also available in most smartwatches (Figure 3e). A soft, free-hand squeeze could activate a virtual radial menu (in the radius of your forearm). Pivoting your forearm scrolls between the menu items and a hard squeeze selects the current menu item.

6 LIMITATIONS AND FUTURE WORK

Force Level Detection: With our current implementation, per-user training gives the best results. However, the maximum number of distinguishable force levels is 3, including *Soft*, *Hard*, and *No-Action*. We believe that performing *Medium* level force was intrinsically ambiguous for participants, mainly due to the lack of any real-time feedback. Also, multiple fine-grained force levels were not reliably distinguishable across users, but using it as a binary switch (*No-Action* vs. force) is reliable.

Expanding Grasping and Activity Testing Set: To create a more robust system, we need to consider expanding the range of grasping actions used. We also tested our approach in a lab environment. To test the reliability of our system in-the-wild, we need to test it under different scenarios, such as when the person is performing another activity like running, cycling and driving.

Gesture Data Collection Method and User Feedback: In our user study, we asked users to control their own force levels and the duration to perform the gesture. However, future studies would need to ensure more controlled conditions by defining a time limit for performing grasps, providing real-time visual or vibrotactile feedback of the force level generated, as well as recommended force level ranges, where these force levels can be obtained using a Fore Sensing Resistor.

Limitations of PPG Sensors: PPG sensors consume more power than the inertial sensors in the smartwatch. Hence, it is not advisable to keep the PPG sensor running continuously. Future implementations would require a robust and easy way to initialize the PPG sensor when needed, such as using a special gesture captured by the inertial sensors as the delimiter of force-based interaction. Future applications could also use context information, such as the users' calendar events (busy vs. free), or the users' activities (running, driving vs. in an office) to decide whether to enable force-based interaction in addition to conventional ways of interaction.

7 CONCLUSION

In this paper, we explored the feasibility of using the PPG sensor of off-the-shelf smartwatches to detect different force levels exerted by the hand when performing different gestures. When running across users, our method is able to reliably detect whether a gesture is performed with extra force, and differentiates between two levels of the extra force. We showed several applications which can benefit from PPG-based force detection. Our system potentially enhances the expressiveness of hand gesture interactions and unlocks a new dimension of force for interactions using smartwatches.

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