# HIPPO: Pervasive Hand-Grip Estimation from Everyday Interactions

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# HIPPO: Pervasive Hand-Grip Estimation from Everyday Interactions

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Hand-grip strength is widely used to estimate muscle strength and it serves as a general indicator of the overall health of a person, particularly in aging adults. Hand-grip strength is typically estimated using dynamometers or specialized force resistant pressure sensors embedded onto objects. Both of these solutions require the user to interact with a dedicated measurement device which unnecessarily restricts the contexts where estimates are acquired. We contribute HIPPO, a novel non-intrusive and opportunistic method for estimating hand-grip strength from everyday interactions with objects. HIPPO re-purposes light sensors available in wearables (e.g., rings or gloves) to capture changes in light reflectivity when people interact with objects. This allows HIPPO to non-intrusively piggyback everyday interactions for health information without affecting the user's everyday routines. We present two prototypes integrating HIPPO, an early smart glove proof-of-concept, and a further optimized solution that uses sensors integrated onto a ring. We validate HIPPO through extensive experiments and compare HIPPO against three baselines, including a clinical dynamometer. Our results show that HIPPO operates robustly across a wide range of everyday objects, and participants. The force strength estimates correlate with estimates produced by pressure-based devices, and can also determine the correct hand grip strength category with up to 86% accuracy. Our findings also suggest that users prefer our approach to existing solutions as HIPPO blends the estimation with everyday interactions.

CCS Concepts: • **Human-centered computing** → *Ubiquitous and mobile computing design and evaluation methods.*

Additional Key Words and Phrases: Light reflectivity, Light scattering, Hand grip strength, Internet of Things, Smart ring

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## 1 INTRODUCTION

The human hand is exceptional. Besides allowing us to interact with everyday objects and perform numerous activities [12, 50], it can also be used as an indicator of human health. Indeed, the force that a person generates through grip, can indicate not just the strength of the hand, but also serve as an early indicator of a wide range of health conditions [36, 37]. Among others, hand-grip strength has been linked to muscle loss [46], a decline of mental cognition [1] and onset of diabetes [30]. Besides serving as a direct indicator of health, hand-grip strength also has other clinical uses. For example, stroke rehabilitation can use hand-grip strength to assess the performance of the upper motor system [2, 16].

Current solutions for estimating an individual's hand-grip strength are cumbersome to use as they are restricted to specific contexts and require interacting with a dedicated object. For example, the most common approach for estimating hand-grip strength is to rely on a dynamometer, which is a clinically certified measurement device. The dynamometer produces a score (unit kg or lb) which is then converted into a categorical grip strength assessment (e.g., weak, normal, strong) according to normative reference tables obtained from large-scale clinical studies [35, 42]. While easy-to-use and accurate, its usage is restricted to medical environments and is mostly only used as part of health checks as a separate measurement device is required. Dynamometers also are laborious to use as they require periodic re-calibration and as the measurements must be taken following a stringent test protocol. While some efforts have been made to provide easier access to hand-grip estimates, e.g., through dynamometers connected to smartphones [13], these similarly require interactions with a dedicated measurement device and are prone to inaccuracies in the measurements. The main alternative is to rely on an object that embeds pressure sensors (i.e., force resistors), but these similarly require interactions with dedicated objects or wearing a device that integrates the sensors at grip contact points and are mostly tailored to specific application scenarios, such as remote surgery [10].

This paper contributes HIPPO as a novel light sensing based approach for estimating the hand-grip strength category of an individual. Humans touch many different objects every day, ranging from personal possessions to home appliances, food items, clothing and so forth [50]. HIPPO exploits these interactions to opportunistically estimate hand grip information from interactions with such everyday objects. The intuition is to re-purpose light sensors that are readily available – or that can be easily integrated – on smart rings, gloves, and other wearables to monitor changes in light reflections from the surface of an object as the individual interacts with the object by gripping and squeezing it. This makes it possible to use a wide range of everyday objects, such as, clothes, disposable cardboard cups, and food packaging to piggyback hand-grip information. We develop two proof-of-concept prototypes that harness this principle. Our first and earlier prototype takes advantage of light sensors integrated into an outdoor glove, and our second prototype further optimizes the form-factor and integrates the sensors onto a ring that is combined with a smartwatch type of device that is responsible for controlling the sensor. We also describe the design of the underlying sensing pipeline.

We validate and demonstrate the benefits of HIPPO through rigorous experiments that consider hand-grip measurements from 44 participants (smart glove: 24 and smart ring: 20). As part of the experiments, we compare our approach against several baselines, including a clinical dynamometer and custom objects that integrate pressure sensors. The results demonstrate up to 86% accuracy in determining the hand-grip strength category of an individual and a close correspondence between changes in light intensity values and the pressure exerted by the individual on an object (RMSE 2.57 - 9.89 depending on the extent of side information that is available). HIPPO significantly improves on a pressure sensor based baseline and produces hand-grip estimates that are comparable to a clinical dynamometer used as the gold-standard. We also show that HIPPO operates robustly across a wide range of everyday objects and participants with different characteristics. Taken together, our results demonstrate that using light reflectance resulting from everyday interactions is a promising solution for opportunistic capture of hand-grip characteristics and for achieving unobtrusive monitoring of an important health parameter.

Summary of Contributions:

- **Novel method and sensing modality** for capturing hand grip strength opportunistically using light reflectance measurements resulting from everyday interactions with objects.
- **Novel insights** into light sensing by demonstrating that the changes in the surface of objects captured by light measurements correlate with hand-grip strength measurements, as given by a clinical baseline.
- **Extensive benchmarks** demonstrate that light sensing provides better performance than pressure sensors and is comparable to a clinical dynamometer.

## 2 RELATED WORK

**Hand patterns and activity recognition:** Human activity recognition have been studied extensively from simple activities, such as walking, to more fine-grained activities, such as folding clothes [3]. Hand posture and pressure are relevant to analyze situational impairment that can hamper interactions with mobile applications [17]. Motion sensors along with gesture interactions with screens have been studied to identify hand patterns [27]. Electromyography sensing also has been proposed to detect holding patterns of objects [14]. Squeeze gestures have been studied to understand the human grip for holding smartphones [39]. Pressure information from hand-grip and fingers have been analyzed for interactive interfaces [43, 44]. New wearable devices also have been studied to capture information from the human hand [28]. Unlike these works, we focus on hand-grip strength as it simultaneously provides health information.

**Hand-grip and health:** Hand-grip strength has been shown to be a good indicator for diagnosing multiple health conditions. The most evident condition that can be monitored is the loss (or gain) of muscle strength over time [47]. Typically, loss of muscles occurs as individuals age or get drastically ill [5, 6]. Hand-grip strength can also provide insights into the cognitive function of individuals as they get older. More severe conditions can also be predicted through the monitoring of hand-grip strength [36]. For instance, it has been studied that obesity changes the structure of the hand, and thus it can influence hand-grip strength [46]. Likewise, cardiac disorders have been linked to low hand-grip strength in individuals [36, 38]. Other studies also have demonstrated the importance of hand-grip strength by using it as a predictor to identify diabetes, respiratory diseases and even cancer [8, 30, 45]. Due to the simplicity of measuring hand-grip strength, it is a test that can be used to easily monitor the health of a population [35]. In our work, we design and develop an approach that can be embedded in wearable devices, such as smart rings and gloves, such that hand-grip strength can be monitored continuously.

**Pervasive digital health:** Research in pervasive health has steadily evolved [4, 34]. As smart devices have become pervasive tools to collect personal data from individuals continuously, numerous sensors have been piggybacked and re-purposed to monitor several health aspects of individuals. For instance, light sensors can be used to collect heart rate measurements and analyze blood stream and glucose of individuals [18, 23]. A camera also has been shown to be useful to obtain sample measurements to estimate heart rate [25]. With this information collected over time, several conditions that affect human health have been studied. For instance, heart rate measurements can be easily collected by hand wrists and smart watches to diagnose sleep deprivation and stress [22, 41]. Heart rate also has been estimated solely by grabbing a smartphones [26]. Respiratory information has been collected through the microphone of smartphones to diagnose respiratory diseases [20, 21], e.g., COVID-19. Motion sensor information from smartphones has been analyzed to diagnose Parkinson's disease [31]. Passive thermal imaging have been also investigated to extract temperature from objects touched by humans [9, 12]. Other smartphone solutions have been designed to capture the physical conditions of individuals, e.g., eating activities [49]. Unlike previous work, our work focuses on measuring hand-grip strength using light sensors.

Table 1. Hand-grip measurements from participants across different days. *DH: Dominant Hand*, *R: Right*, *L: Left*.

| Participants | | day1 | | day2 | | day3 | | day4 | | day5 | | day6 | | day7 | | day8 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **id** | **DH** | **L** | **R** | **L** | **R** | **L** | **R** | **L** | **R** | **L** | **R** | **L** | **R** | **L** | **R** | **L** | **R** |
| 1 | Right | weak | weak | weak | normal | weak | normal | weak | normal | weak | normal | weak | normal | weak | normal | weak | normal |
| 2 | Right | normal | normal | normal | normal | normal | normal | normal | normal | normal | normal | normal | normal | normal | normal | normal | normal |
| 3 | Right | weak | weak | weak | normal | weak | weak | weak | weak | weak | weak | weak | weak | weak | weak | weak | weak |
| 4 | Right | weak | normal | weak | normal | normal | normal | normal | normal | weak | normal | normal | normal | normal | normal | weak | normal |
| 5 | Right | weak | weak | normal | normal | weak | normal | weak | normal | weak | normal | weak | normal | weak | normal | weak | normal |
| 6 | Right | weak | weak | normal | normal | normal | normal | normal | normal | weak | normal | weak | weak | normal | normal | weak | weak |
| 7 | Right | weak | weak | weak | weak | weak | weak | weak | weak | weak | normal | weak | normal | weak | weak | weak | weak |
| 8 | Right | weak | weak | weak | weak | weak | normal | weak | weak | weak | normal | weak | normal | weak | normal | weak | normal |
| 9 | Right | weak | weak | weak | weak | weak | weak | weak | weak | weak | weak | weak | weak | weak | weak | weak | weak |
| 10 | Right | normal | normal | normal | normal | normal | normal | normal | normal | normal | normal | normal | normal | normal | normal | normal | normal |

## 3 MOTIVATION

Previous research suggests that hand-grip characteristics may be dependent on the context where they are taken, with particularly the posture of the user, the time-of-day, and prior activity being factors that can affect hand-grip characteristics [11]. On the other hand, there is evidence to suggest that hand-grip strength is generally consistent over time, as long as the context remains sufficiently similar [7]. We first demonstrate that robust hand-grip assessments are possible by carrying a small-scale study that shows hand-grip assessments to be consistent also when taken outside of a medical environment, even when taking in different days, using different postures, or different times-of-day. We next detail our experiment and its results.

**Setup:** We recruited 10 participants and measured their hand-grip strength 8 times during a two-week period. The mean age of the participants was 29.6 (standard deviation 7.78). The time-of-day for the measurements was varied to ensure any variations resulting from daily fluctuations would be captured. During each measurement period, hand-grip was assessed six times in total, three times each for left and right hands. All measurements were taken using a dynamometer. The dynamometer requires the participants to follow a simple but precise procedure (See Section 5 and 6 for a description about the apparatus and procedure). At the beginning of each measurement period, the dynamometer was configured according to the gender and age of each participant. The grip area of the dynamometer was also adjusted for each participant until the second joint of the index finger was at a 90 degree of the handle. After this, each participant performs the dynamometer procedure and measurements were recorded. The grip measurements were also classified into one of three categories following the common methodology for assessing the physical status of a person [35, 40]: *weak, normal and strong*. This is accomplished by configuring the dynamometer with the relevant user characteristics, and mapping the score produced by a dynamometer to a category through a normative reference table that accounts for variations in user characteristics.

**Results:** Table 1 shows the results and separately includes information about the dominant hand (DH) of the participant and grip strength measurements for the left (L) and the right hand (R). The dominant hand generally outperforms the weaker hand, which shows the measurements process to be accurate. In line with results in medical studies [7], the measurements are highly consistent across different days despite being taken at different-times-of-day. The only variations we observe are shifts between adjacent categories, e.g., there are some cases where we can observe a shift from weak to normal or vice-versa. These findings suggest that hand-grip is generally sufficiently consistent and that the variations caused by different contexts are generally small. However, the results also suggest that hand-grip strength should be sampled multiple times in different contexts to minimize the influence of any situational factors. Our approach is well-suited for this purpose as it opportunistically harnesses everyday interactions which take place in wide range of contexts, thus offering ample data to overcome situational influences in the measurements.

## 4 PERVASIVE HAND-GRIP STRENGTH MONITORING

The proposed method for hand-grip strength estimations takes advantage of the fact that interactions with certain objects result in topological transformations in the shape of the object and that these changes can be captured through light reflectance [51]. The amount of force that is applied on the object influences the extent of change in the shape, and this in turn affects the amount of light that is reflected by the surface of the object (Figure 1(a)). Examples of this kind of interactions include crumpling, squeezing and pressing down objects such as packaging or clothes. In the rest of this section, we briefly explain the theoretical foundation of our solution, and present the algorithmic pipeline that we use for mapping light reflectance values into hand-grip strength estimates.

**Overview:** The general principle behind HIPPO is illustrated in Figure 1. A light sensor (light source + photoresistor) worn on the user's hand, e.g., integrated onto the exterior of a smart glove or a smart ring, is used to measure changes in light reflectance as the user interacts with (malleable) objects. When the object is held in hand normally, the surface of the object covers the light sensor and the intensity of the reflected light is (approximately) constant and this value is used as reference value for estimating overall hand grip strength. As the user grips the object, the surface of the object changes. The extent of these changes depends on the force that is applied on the object, as well as the material of the object. Changes in the surface of the object affect the intensity of the reflected light as the sensor is in closer contact to the object and as the refraction and reflection patterns from the object's surface change. As the pressure on the object is maintained, the changes in the surface and consequently also the intensity of the reflected light become (approximately) constant. HIPPO monitors for these changes in light reflectance, and estimates the hand grip strength opportunistically using differences between the intensity at initial and maximal strength.

When users grab an object, the overall force exerted on the object is distributed among the different fingers grasping an object and the distribution of force along the different fingers further depends on the nature of the interaction as well as the surface material of the object [29, 33]. Optimally the measurements would be taken from all fingers, or from the thumb since that tends to have the highest overall contribution. In practice, the sensors need to be integrated with a device that is easy to wear with a smart ring or a wearable glove being the most practical approaches. As part of our experiments, we separately consider measurements from three different fingers to demonstrate the practicality of our approach. Specifically, we consider measurements from the index, middle and little finger as these are the three most important fingers (referred to as position-1 to position-3) in Figure 1(b) for hand grip. Index finger typically serves as the first point of contact with the object, but it tends to have the smallest overall contribution. The middle finger tends to have the most consistent contribution to grip strength, whereas the contribution of the little finger depends on the nature of the task with the contribution being largest in tasks that require careful finger coordination.

**Theoretical Foundation:** HIPPO estimates hand-grip strength from changes in light reflectivity induced on the surface of an object [15]. As a beam (source) of light is pointed to a surface, the light is reflected back from the surface. When an individual interacts with an object, e.g., by squeezing it, the interaction results in a pressure ($P$) being applied to the object. The grip exerts a force ($F$) over the surface area of the object ($S$), which in turn results in a deformation of the surface area $S$ of the object. The extent of this deformation is indicative of the force that is being applied. Formally, this relation is given by $P = \frac{F}{S}$. Deriving an exact estimate of $F$ would require knowing the surface area that is being measured. Instead, HIPPO uses the changes in light intensity as input to machine learning algorithms to estimate the hand-grip strength and the appropriate category (weak, normal, strong) of the individual's hand-grip strength.

**Sensing Pipeline:** Figure 2 illustrates the sensing pipeline from data collection to signal processing and eventual estimation of hand-grip strength. The pipeline operates using light sensors that comprise of a light source and a photoreceptor. As we measure reflections from objects that the user interacts with, the sensor needs to be on

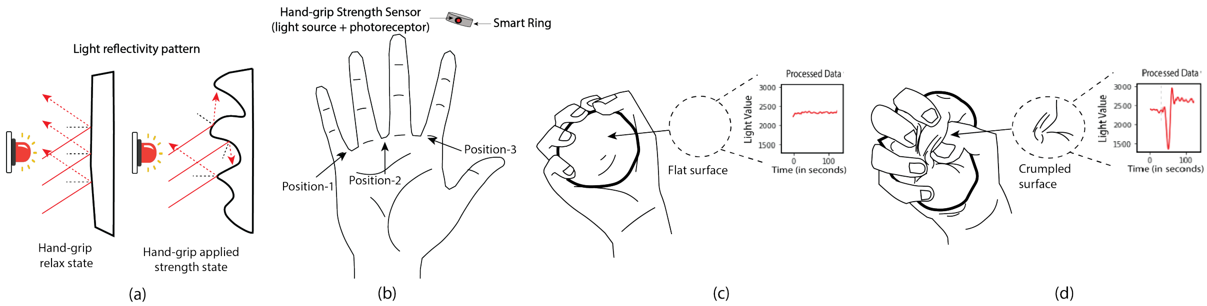



Fig. 1. Pervasive hand-grip strength analysis, a) Light reflectivity pattern of the object in different states, b) Available positions in hand for light sensing deployment, c) Hand-grip relax state, d) Hand-grip applied strength state.

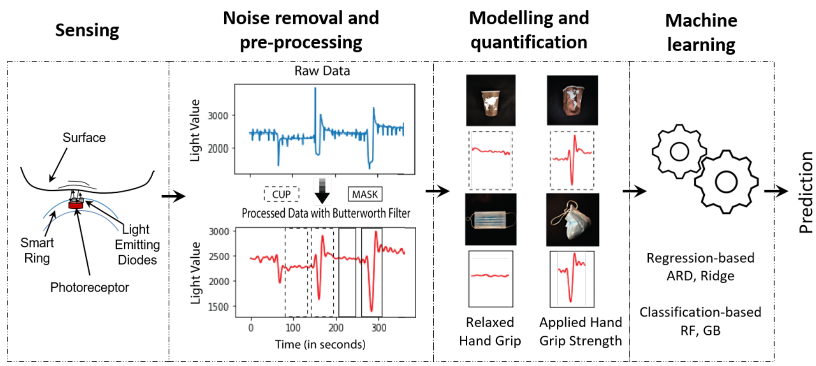



Fig. 2. Sensing pipeline for processing sampling of hand-grip strength.

the exterior of the device integrating them and face outward from the user's hand. In practice, also a proximity sensor should be integrated on the device to minimize unnecessary sampling.

Our implementation of the sensing pipeline detects interactions with malleable everyday objects from the light intensity measurements and processes these to estimate hand-grip strength. First, interactions can be detected from peaks in the intensity measurements. We then find a rest point where the hand is holding the object, but not yet squeezing or applying pressure on it (Figure 1(c)). This forms a reference point for analysing the overall force that is exerted. Once the individual exerts a force on the object, the shape of the object starts to deform and this results in changes in the reflected values (Figure 1(d)). These changes comprise the input to the sensing pipeline. Since hand-grip strength measurements are provided by a quick grip (following certified dynamometer procedure), only measurements that are provided below the 2-3 seconds range are considered as valid measurements that depict hand-grip strength. In line with established practices [32], the light measurements are first cleaned using Butterworth and Chebyshev filters. Next, light patterns that depict hand-grip strength are labelled as relaxed hand-grip or applied hand-grip. This data is then used to construct standard machine learning regressors for estimating hand-grip strength: Automatic Relevance Determination Regression (ARD), and Ridge Regression (Ridge). This data is also used to classify hand-grip strength categories using two common classifiers: Random Forest (RF) and Gradient Boosting (GB). Note that while the intensity measurements are dependent on the location of the sensor, the pipeline itself is agnostic of the sensor location and can operate using measurements from multiple different positions.

## 5 PROTOTYPE DESIGN AND BASELINES

The possible design space for our solution is immense as the only requirement is having a light sensor (i.e., light source and photoreceptor) relatively close to the surface of the object that is being interacted with. Our contribution focuses on demonstrating the principle of using light reflections for estimating hand-grip strength, and for conducting our experiments we implemented a proof-of-concept prototype that integrates three light sensors on a smart glove. The glove allowed us to place multiple sensors simultaneously on the object and evaluate the impact of sensor orientation relative to the object on the estimation performance. In practical use we would expect our solution to be integrated to a smart ring or other hand worn wearable and the sensors in our prototype have been placed on different fingers to emulate how rings would be worn – as well as to evaluate the robustness of our approach against changes in hand position. We next describe the prototype and the baselines our system is compared against in the experiments.

### 5.1 HIPPO Prototype Design

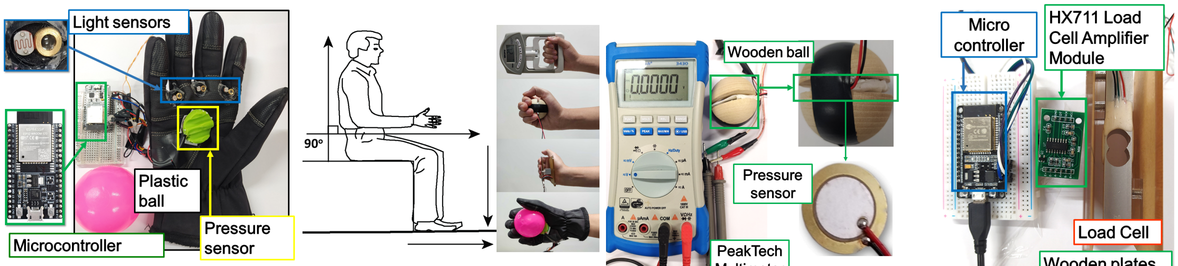
The prototype shown in Figure 3(a), consists of a glove that integrates three light sensors connected to an ESP32 development board. The key reason for using a glove is that it can be easily extended with multiple sensors to provide measurements simultaneously from different angles. The board controls the sampling frequency and uploads the collected data to a web server in real-time. Each light sensor consists of a red laser diode (650nm, 5mW, $3 - 5$V) and a GM5539 photo-resistor (5MΩ). The light sensor is easy to deploy, and the components are also low cost, which makes our solution affordable and easy to scale, e.g., a pack of 10 lasers and 20 photo resistors costs around 10 US dollars. We use the ESP32 development board as a microcontroller because of its inbuilt Wi-Fi connection facility and it provides multiple inputs to connect multiple sensors at the same time. Each photo resistor changes its resistance according to light intensity, and we use this to measure reflected light. The ESP32 reads photo resistors' values and forwards the values to a web server together with a timestamp. By default, the photo resistor captures analog voltage measurements, which are then changed to digital voltage representations. We use the output value of the ADC (analog to digital conversion, with a resolution of 12 bits, i.e., the voltage is discretized to 4096 levels) as the physical unit to represent the intensity of reflected light. The glove is also equipped with a piezoelectric sensor located on the palm. Data from the sensor is collected using a Multimeter PeakTech 3430 that measures real time voltage with a timestamp. Collected data from the pressure sensor and light sensors are synchronized to analyze hand-grip strength from different sensing angles. The sampling rate of the sensor is 5Hz, and we found that about 50 samples on average are necessary to characterize the strength applied on an object with 97.5% confidence.

In our main controlled experiment, the glove is used alongside a plastic ball that is partially inflated. When the plastic ball is held in hand without any exertion, this provides a reference point that can be used to quantify hand-grip strength. Once a force is exerted, the surface of the object changes, and this can be simultaneously measured by changes in the internal air pressure and changes in the reflected light. Internal air pressure is measured using a pressure gauge tool (Kixre Digital Tire Pressure Gauge). The device measured 0 PSI units when the ball was held, and up to 9.9 PSI when it was squeezed. Later we also conduct separate experiments where we consider a wide set of everyday objects instead of an inflatable ball.

### 5.2 Baselines

*5.2.1 Dynamometer (Baseline 1).* To verify the performance of HIPPO, an off-the-shelf commercial dynamometer is used to obtain valid reference measurements that depict hand grip strength (gold standard). We used the GRIPX EH101 dynamometer[1] that is shown in Figure 3(b). The dynamometer measures hand-grip strength in kilograms (kg) and has a measuring capacity of 198lbs (90kgs). The device is certified to produce highly accurate

[1] https://gripx.net/




(a) Light sensing (b) Body position and baselines (Baseline 1 on the top) (c) Baseline 2 (d) Baseline 3

Fig. 3. Prototypes used to measure hand-grip strength: (a) HIPPO prototype integrated onto a wearable (glove); (b) Dynamometer baseline; (c) Wood ball baseline; and (d) Pressure plate baseline.

measurements. The dynamometer maps the grip strength into one of three categories for grip strength (weak, normal, and strong) based on normative grip-strength tables. Since these tables are dependent on age and gender, the dynamometer needs to be configured separately for each individual prior to using it.

*5.2.2 Wooden Ball (Baseline 2).* The second baseline is a squeezable stress-ball type of design shown in Figure 3(c). The object is designed using wood, resulting in an even distribution of pressure along the surface. Indeed, many other materials absorb some of the pressure and can mislead the pressure readings. Note that this only affects the baseline that uses pressure sensors, and not the use of light reflectance measurements. The wooden ball was cut into halves and a piezoelectric pressure sensor was placed in between them. The piezoelectric sensor exploits mechanical stresses by measuring the voltage across a piezoelectric element generated by the applied force. We record the induced voltage, measured in millivolts (mV), using a Multimeter that connects to a computer with one mega ohm resistor in between to get a real time log of voltage readings with its respective timestamp.

*5.2.3 Pressure Plates (Baseline 3).* Our final baseline consists of wooden pressure plates. The prototype is shown in Figure 3(d) and uses the dual-channel 24 Bit HX711 load cell amplifier module, and a Bending Beam Load Cell (straight bar load cell). A load cell is a transducer device, which converts mechanical force into a measurable electrical output in response to, and proportional to, the force applied to it. We mounted the load cell in between two wooden plates so that when pressure is applied to the wooden plates, it will pass to the load cell. Since the load cell output is very small, we use the HX711 load cell amplifier that helps the microcontroller read the changes in the resistance of the load cell and get very accurate load measurements. Once the pressure is applied to the load cell, the microprocessor can read the corresponding discrete-valued voltage (as given by the ADC output) and upload this value to the Web server with a timestamp.

## 6 SMART GLOVE EXPERIMENTS: ROBUSTNESS OF HAND-GRIP STRENGTH ESTIMATION

We first conduct experiments with $N = 24$ participants that focuses on assessing the robustness and accuracy of using light reflection measurements to estimate hand-grip strength. These experiments are conducted using a smart glove prototype integrating HIPPO. We later further explore a smaller and more practical prototype that integrates HIPPO into a smart ring, and we evaluate how the ring prototype can be used to estimate grip strength from everyday interactions.

## 6.1 Experimental Design

*6.1.1 Study Design.* The experiment is designed as a within-subject design where participants perform hand-grip force measurements with four different devices at two different times-of-day and days. We encode the data as a $1 \times 2$ factorial design with device type and trial as independent variables as this allows us to evaluate the effect of different devices, times-of-day, as well as to identify potential order effects. The device type variable has four levels, corresponding to our prototype and the three baselines: Smart glove (GLOVE), Dynamometer (DYNA), Wooden ball (W-BALL) and Pressure plates (PLATES). The trial variable has two levels, corresponding to the first and second time that the experiment was conducted. To eliminate order effect and biases, whilst keeping the number of trials manageable, trial number was counterbalanced following a Latin Square design, resulting in eight experimental conditions: (1) Trial1-GLOVE, (2) Trial2-GLOVE, (3) Trial1-DYNA, (4) Trial2-DYNA, (5) Trial1-W-BALL, (6) Trial2-W-BALL, (7) Trial1-PLATES and (8) Trial2-PLATES. The trial number was limited to two as the intensity of the hand-grip strength tends to decrease with multiple attempts. We also provide a three minute break between successive tests to change the device and let the muscles relax. For this experiment, $N = 24$ participants were recruited (Males=12, Females=12). The participants were university students and staff from different fields and nationalities. Their average age was $28.5 \pm 3.58$ and all of them were right-handed.

*6.1.2 Procedure.* Before starting the study, the researcher who conducted the experiment demonstrated to the participant how to perform the task and provided a detailed description about how to grab each device. Each participant also signed an informed consent form, following local IRB regulations. Prior to starting the experiment, we used a ruler to measure the hand dimensions (breadth and length) of each participant as this allows us to estimate the total surface area of the hand. Once the participant was ready to start the experiment, the different experimental conditions were presented to participants and the participants carried them out one by one. Each experimental task was carried out similarly to our dynamometer experiments in Section 3 and illustrated in Figure 3(b). Specifically, the participants were asked to sit with feet on the floor and the back touching the chair. The elbow of the (right) hand holding the device measuring hand-grip strength is placed at the participant side at a 90 degree angle. We followed a rapid exchange grip test which requires the participant to apply the maximum grip force on each device for 2 to 3 seconds without holding their breath, and then release the grip and relax. The force applied on each device was recorded. None of these values were reported to the participants in between the experiments to avoid any potential compensation effects. After the experiment concluded, a brief interview with the participant was conducted to analyze the user experience and overall perception of the devices. Upon concluding the experiment, the scores were revealed to the participant (if they were interested in knowing them). The evaluation took place in one university room across one week in time slots between 11:00 and to 07:00 pm. For each participant, the overall experiment lasted 35 min to 40 min.

## 6.2 Analysis and Results

*6.2.1 Stability of Steady-State Estimates.* The capability to estimate force grip strength depends on the potential to obtain an accurate reference measurement when the object is held normally without exerting any additional force. Figure 4(a) and (b) visualize the distribution and variation in light sensor values obtained from the three fingers when the object was held in a relaxed state (i.e., no force exerted). The former focuses on a specific point on the object, whereas the latter depicts different points when hold by different participants. In both figures (a and b), we can observe the variance of the measurements to be low across all fingers but the mean value depends on the finger from which the measurements are. The specific values of the fingers (shown in Figure 4a) are as follows: little finger (position-1, mean=3063.59, SD=27.79), middle finger (position-2, mean=1588.81, SD=22.98) and index finger (position-3, mean=1090.01, SD=34.45). Likewise, we also estimate the light reflectivity values at the different positions as objects are held by different individuals in a relaxed state. Figure 4b shows the results. From the figure, we can observe that there are small variations in light values: Position-1: Mean = 3073.99,

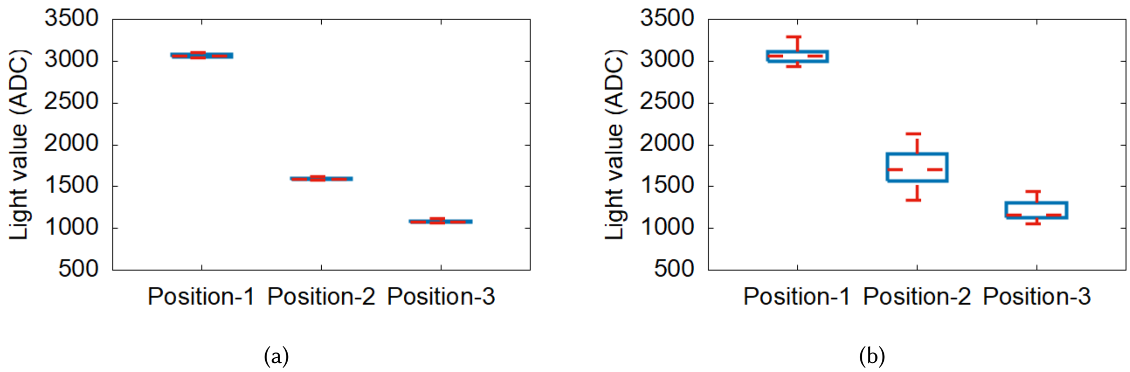


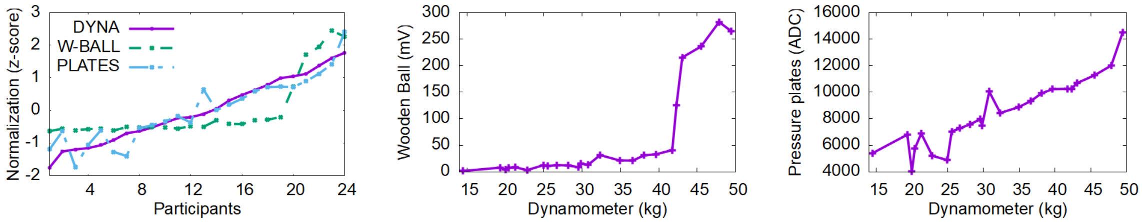

Fig. 4. Capturing hand grip strength, a) Light characterization of different positions (in the relaxed state), b) the variation of light value across all participants in different positions (in the relaxed state).

SD=103.52; Position-2: Mean = 1712.61, SD=215.67; Position-3: Mean = 1205.75, SD=110.92, indicating that stable light values can be captured to derive hand grip strength.

The index and the middle finger have similar patterns, with the index finger resulting in slightly lower intensity as the sensor is better covered by the object when no force is exerted. In contrast, the little finger has highest intensity indicating that less light is blocked by the object. Note that the difference between fingers does not affect the final estimates as the overall force is estimated from changes in intensity of reflected light between maximum and minimum grip force. These results are in line with existing studies on grip distribution [10, 29]. The low variance of the measurements across all fingers shows that the reference point can be estimated robustly, whereas variations across fingers simply highlight how the distribution of force along different fingers is captured by the light intensity values. This indicates that the changes in object surface can be captured accurately irrespective of position, but that the absolute values are sensitive to contact position. As we next demonstrate, the relative values are robust across locations, and hence it is sufficient to have a calibration reference point for a specific position.

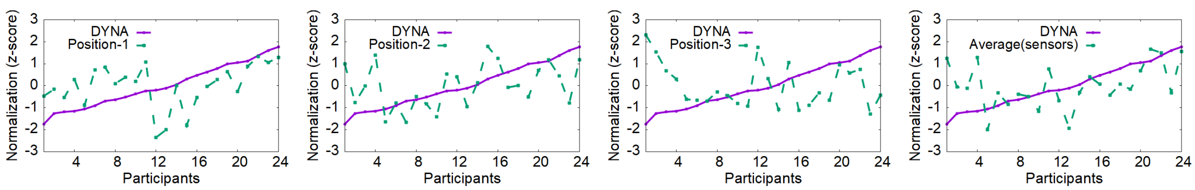
*6.2.2 Baseline and Experiment Validity.* Figure 5(a) shows the hand-grip strength assessments for the baselines and compares them against the dynamometer which serves as the gold standard. As the measurements the devices produce are on different scales, we normalize the data using z-score scaling to make it comparable. We can observe that both the wooden ball and the pressure plates follow the same trend as the dynamometer reference values. As the order of devices was randomized across the trials, the high correspondence between the different devices indicates that the hand-grip values were consistent throughout the experiment and validates our experimental design. In addition, Figure 5(b) and (c) also shows the level of linear relation between the default units of dynamometer (kg) and, wood ball (mV) and plates (ADC), respectively. In our experiments, participants scored between normal and weak types of hand-grip strength.

*6.2.3 Light Measurement Quality.* Next we demonstrate that the light intensity measurements reflect the same differences as what the baselines capture. We use a Kolmogorov-Smirnov test to compare the measurements from HIPPO against each of the baselines. To analyze the effect of different finger positions, we perform the analysis separately for each of the three finger positions considered in our study. The results of the analysis are shown in Table 2. With a single exception (little finger cf. wooden ball), no statistical differences can be observed with the measurements, i.e., they come from a similar distribution. The measurements from different finger positions have high similarity with the dynamometer. The finger positions also have similarity across each other, suggesting that HIPPO can operate well at different finger positions, even if the distribution of force that is captured differs




(a) (b) (c)

Fig. 5. Comparison of different baselines in hand-grip strength assessments, a) normalized comparison, b) and (c) with their respective physical units.




(a) Position-1 (b) Position-2 (c) Position-3 (d) Average (all sensors)

Fig. 6. Hand-grip strength captured by different light sensors in different positions (All the participants).

across fingers. The sole exception in the results is the wooden ball, which overall results in lowest similarities. This is due to the hard surface of the wooden ball. Moreover, a key factor for the lower similarity is that the sensors are inside the ball and the surface absorbs some of the force that is exerted on it. Indeed, the wooden ball also has low similarity with the other baselines, including the clinical dynamometer (gold standard).

Table 2. Data similarity between different sampling devices. Red colours indicate there is significant differences (*p<0.05*). The positions refer to different fingers: little finger (1), middle finger (2), index finger (3).

| **Devices** | | **DYNA** | **W-BALL** | **PLATES** | **GLOVE Sensors** | | |
|---|---|---|---|---|---|---|---|
| | | | | | **Position-1** | **Position-2** | **Position-3** |
| **DYNA** | | 1 | 0.139 | 0.994 | 0.902 | 0.994 | 0.902 |
| **W-BALL** | | 0.139 | 1 | 0.139 | 0.011 | 0.067 | 0.067 |
| **PLATES** | | 0.994 | 0.139 | 1 | 0.902 | 0.994 | 0.902 |
| **GLOVE Sensors** | **Position-1** | 0.902 | 0.011 | 0.902 | 1 | 0.902 | 0.262 |
| | **Position-2** | 0.994 | 0.067 | 0.994 | 0.902 | 1 | 0.902 |
| | **Position-3** | 0.902 | 0.067 | 0.902 | 0.262 | 0.902 | 1 |

*6.2.4 Sensor Position.* Figure 6 shows the results for the different participants for the different fingers and compares the results against the dynamometer reference. The relative patterns align with the dynamometer for most participants, but there are also some deviations from the reference. The best alignment results from using all three positions simultaneously as the optimal finger from which to sample measurements varies across the participants. This is to be expected as the contribution of each finger on the overall force that is applied varies across individuals [10, 29, 29]. Note also that the patterns for the little finger (position-1) and index finger (position-3) are often reversed and the patterns often offset each other. This is due to higher pressure on the index finger resulting in a loosening of the grip at the little finger, and conversely higher force on the little finger indicating a smaller contribution of the index finger. The middle finger is expected to result in the most consistent pattern, but this depends also on the characteristics of the object and the force that is applied on the object. Malleable objects with a soft surface can result in significant changes in the surface of the object and this can decrease the contact of individual fingers. For example, the experiments consider a squeezable ball whose shape undergoes significant changes and this can result in the grip of the middle finger loosening. Nevertheless, as the results indicate, these variations can most of the time be overcome by simply using multiple contact points. Further stability can be achieved by analysing the reflection patterns in more detail and filtering out periods where the reflection characteristics undergo changes.

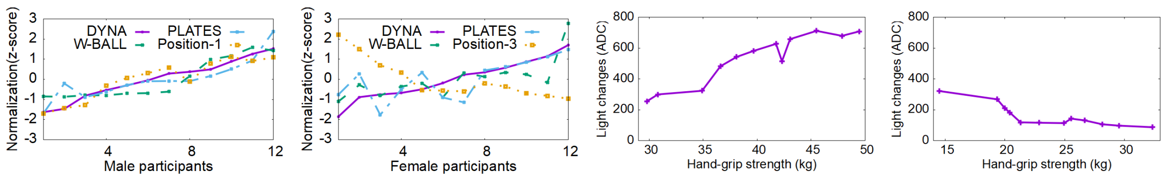
*6.2.5 Individual Differences.* To better understand variations across individuals, we next split the participants into two groups based on gender (Figure 7). Figure 7(a) and (b) compares (on a normalized scale) the hand-grip data captured by all the devices. In parallel to this, Figure 7(c) and (d) show the level of linearization between the dynamometer and the light reflectivity values with their actual physical units. This group (male and female) division is motivated by the fact that hand size and physical strength are governed by gender characteristics [48]. Table 3 shows the Kendall correlation of the measurements when the participants are grouped and Table 4 shows the results without grouping. The results show that the correlations for index (position-3) and little finger (position-1) are significantly higher when the participants are grouped by gender. Note also that the sign of the correlation changes (for both genders) depending on the finger. A negative correlation indicates a reduction in light intensity as force is applied, which indicates a closer contact between the sensor and the surface of the object. Positive correlation, in turn, means the contact is not as tight which results in higher amount of light reflecting back to the receptor – as well as small amounts of ambient light being able to enter the sensor. This also further explains why the variations in the index and little finger measurements, as discussed above, tend to offset each other.

To further understand the differences, we next calculate the DYNA-hand which briefly estimates the pressure on the objects based on the hand size. DYNA-hand is the value of dividing the dynamometer reading (force) with the hand size which is calculated from the hand dimensions collected prior to the study (hand-size $\approx$ hand-length $\times$ hand-breadth, DYNA-hand = $\frac{DYNA}{hand-size}$). Table 5 shows the similarity values (from a Kolmogorov-Smirnov test) and also the correlation analysis (Kendall). The similarities are high for all finger positions and both genders, highlighting that the general principle of using light intensity variations is viable means of estimating changes in grip force. The extent of changes depends on the surface area of the hand, and using the gender of the participant tends to serve as a proxy to these changes. Naturally estimating the surface area of the hand is infeasible on a simple wearable sensor. The most practical way to overcome this limitation is to (i) select sensor position based on hand-size or (ii) collect measurements from multiple positions simultaneously and (iii) adapt the analysis according to variations in the light intensity values. For people with smaller hand, the increase in grip at index finger seems to be best indicative of grip force, whereas for people with larger hand size the grip force can be reliably estimated from the loosened grip at the little finger. In addition, we can observe the significant correlation between the light sensor in position-1 and DYNA-hand. Figure 8 also shows the strong relation in position-1 especially when the gender is considered. However, there is no significant correlation for other positions, except the female participants in position-3. Therefore, we can conclude that the position-1 can achieve the best hand-grip strength estimation, which will be further proved in the following.

*6.2.6 Comfort in Capturing Hand-grip Strength.* Besides individual differences of participants, we explored the user experience by measuring the comfort (or discomfort) of performing the hand-grip strength experiments with the different devices. As a dynamometer has a flexible ergonomic design to adapt easily to any individual, it is important then to analyze the perception of participants when using the devices. To do this, after the

Table 3. Correlation (Kendall) coefficient ($\tau$) analysis for all devices (Divided by group)

| Devices | GLOVE Sensors (Male) | | | GLOVE Sensors (Female) | | |
|---|---|---|---|---|---|---|
| | Position1-M | Position2-M | Position3-M | Position1-F | Position2-F | Position3-F |
| **DYNA** | 0.85 | 0.03 | -0.21 | 0.33 | -0.12 | -0.82 |
| **W-BALL** | 0.76 | 0.06 | -0.18 | 0.18 | -0.48 | -0.58 |
| **PLATES** | 0.79 | -0.09 | -0.21 | 0.09 | 0.06 | -0.45 |




(a) Male in position-1 (b) Female in position-3 (c) Male in position-1 (d) Female in position-3

Fig. 7. Hand-grip analysis divided per group using the best sensor per group, a) and b) with normalization, c) and d) with physical units.

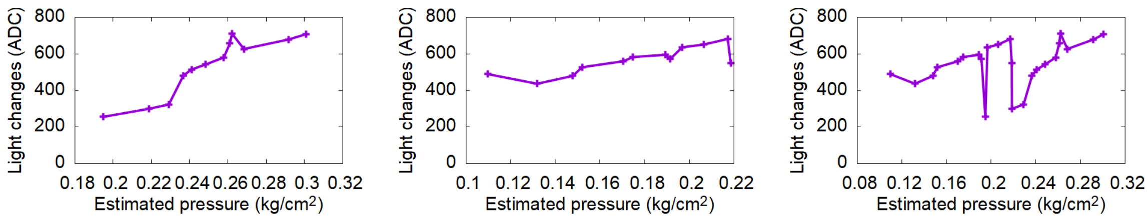
Table 4. Correlation (Kendall) coefficient ($\tau$) analysis for all devices.

| Devices | DYNA | W-BALL | PLATES | GLOVE Sensors | | |
|---|---|---|---|---|---|---|
| | | | | Position-1 | Position-2 | Position-3 |
| **DYNA** | 1 | 0.86 | 0.86 | 0.29 | 0.19 | -0.21 |
| **W-BALL** | 0.86 | 1 | 0.80 | 0.25 | 0.15 | -0.13 |
| **PLATES** | 0.86 | 0.80 | 1 | 0.22 | 0.20 | -0.13 |

Table 5. Statistical analysis between light reflectivity changes in different positions and DYNA-hand (value of dividing the dynamometer value with the hand size): red colour indicates lack of statistical significance in similarity or correlation.

| Statistical Analysis | Position-1 | | | Position-2 | | | Position-3 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Male | Female | All | Male | Female | All | Male | Female | All |
| **Similarity** | 0.998 | 0.998 | 0.994 | 0.998 | 0.998 | 0.902 | 0.998 | 0.536 | 0.902 |
| **Correlation** | 0.88 | 0.67 | 0.39 | -0.12 | -0.09 | 0.14 | -0.36 | -0.73 | -0.23 |

experiment finalized, we ask all the participants to assign rankwn values (on a 4-point Likert scale) based on their comfort when using the devices. The scale is anchored at 1 (very uncomfortable) and 4 (very comfortable). Figure 9 shows the results. Overall, the participants ranked the glove as the most comfortable, specially male participants. P3 mentioned that *"squeezing everyday objects is a very non-intrusive way because it is not noticeable"*. Another participant P12 also mentioned that *"the glove is very a lightweight solution"*. In contrast, there were also participants that disliked the glove, specifically female participants. P7 mentioned that *"it is difficult to squeeze the plastic ball as its too big for my hands"*. Another participant P20 said that *"I cannot apply proper hand-grip strength as the plastic ball is slippery"*. P18 also said that *"the plastic ball is too soft and it is difficult to assess whether I am applying my maximum hand-grip strength or not"*. In the case of the other devices, W-BALL was ranked as the second most preferable option, specially from female participants. Indeed, P9 mentioned that *"the wooden ball is small enough and provides better control when squeezing the object"*. Several participants also mentioned that *"the wooden ball is painful and hurts the hand as the material is too rigid"*. PLATES and DYNA received almost the




(a) Male participants (b) Female participants (c) All participants

Fig. 8. Estimated pressure on the object (DYNA-hand) captured by the light senor in position-1.

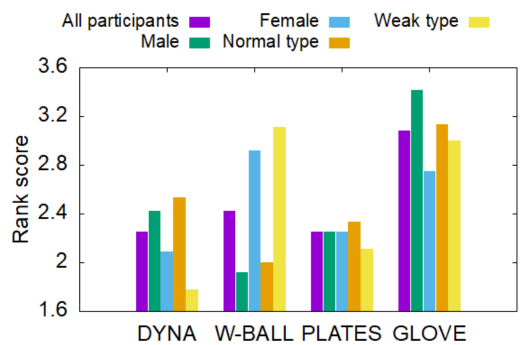



Fig. 9. Ranking of 4 devices in use (the most comfortable–4, the least comfortable–1).

same scores. The main comments about PLATES were that *"it is not easy to press and the shape square design hurts the hand"*. Likewise, the main comments about DYNA were that *"it is too heavy, it seems that the design is not balanced (the frontal part is more heavy than the back one) and it is difficult to provide hand-grip strength as it is too rigid"*. Overall, HIPPO provides the least intrusive and easiest-to-use solution and is preferred by the user compared to the baseline approaches.

*6.2.7 Hand-Grip Strength Estimation (Classification).* Hand grip strength is typically reported using discrete categories that offer a standardized and normative point for comparison. We next demonstrate how HIPPO can support coarse-grained classification of hand grip strength into different grip categories. We use four parameters for prediction: light values (L), gender (G), hand size (S), age (A), and three sensor positions: little finger, middle finger and index finger. Gender and age are well-known to affect hand-grip strength with normative reference tables typically considering these two variables to characterize the hand grip values [35]. Normative values also typically separate values depending on height, and potentially also weight. Height correlates strongly with hand size and thus the use of hand size indicator is equivalent to the use of height as part of dynamometer procedures [19]. We consider two simple machine learning classifiers: Random Forest and Gradient Boosting to guarantee that models can be deployed in low-power environments and 5-fold cross validation to evaluate the generalization of the models. When we train a L-G-S specific model, the average performance for the different fingers is 80% (little finger: 86%, middle finger: 70.5%, index finger: 84%). Once we train a model that considers the relationship between the strength and the age given by the dynamometer norm, L-G-S-A model, the average performance increases to 83% (little finger: 86%, middle finger: 79%, index finger: 84%), indicating the importance of age in strength type classification. In terms of gender, the average classification performance for male participants results in 86.1% (little finger: 91.7%, middle finger: 75%, index finger: 91.7%) and for females 79.2%, (little finger: 79.2%, middle finger: 83.3%, index finger: 75%). These results confirm not only the influence of sensor positions, but also the information that gender can provide into the model. Naturally, other context issues might affect the estimates (e.g., object size, fit of the glove). Overall, the results demonstrate that hand-grip strength can be accurately estimated using HIPPO and especially when the sensor is worn in the little finger.

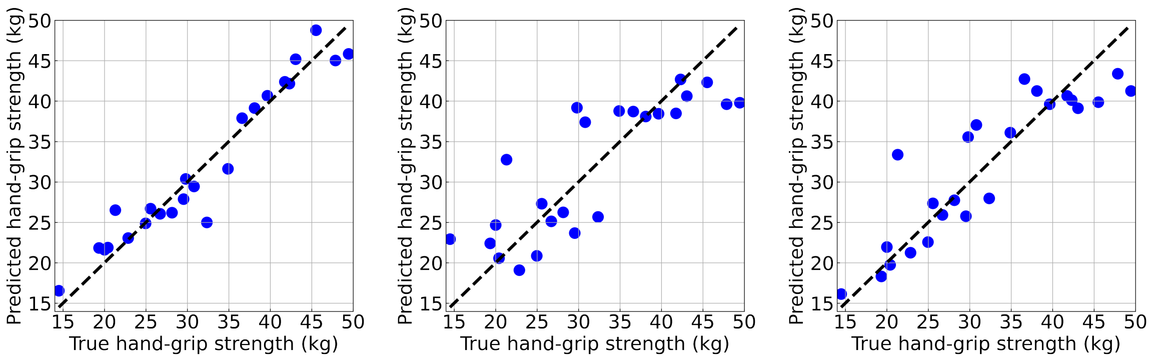
*6.2.8 Hand-Grip Strength Estimation (Regression).* We next demonstrate the potential of using machine learning to estimate the *exact* hand-grip strength based on light measurements and information about the characteristics of the participants. We considered two common regression models (ARDRegression and Ridge) to predict hand-grip strength by 10-fold cross validation across participants (i.e., both trials from each participant were always kept in the same fold to minimize correlations in the test and training sets). We also normalize the input parameters (hand size and lighting values) for more robust regression performance. The regression model effectively provides a mapping that can be used to convert the light reflectivity values captured by the sensor to a physical unit through a correspondence with another measurement device. The root mean square error RMSE (unit kg) and $R^2$ score of the regression experiments are shown in Table 6. When only the light reflectivity changes are considered, the average RMSE is 9.72 kg and the $R^2$ score is 0.01 across all regressors in different positions. This depicts a simple model that estimates hand-grip strength with minimal information about the individuals. Once an additional parameter gender or hand size is considered in the model, the average of RMSE decreases significantly for all positions (gender: RMSE = 4.72 kg, hand size: RMSE = 5.96 kg) with higher model relevance (gender: $R^2$ score = 0.75, hand size: $R^2$ score = 0.63). This supports the insight that individual physical characteristics may improve the regression model further. The best regression performance is achieved in all positions by including more than two factors, being light reflectivity changes (L), gender (G) and hand size (S) and the performance can be further improved when more measurements are taken. The best results are obtained for the little finger: RMSE 2.57 kg and $R^2$ score 0.93 across both regressors. Since different finger positions influence the hand-grip strength estimates, we also evaluate regression performance for measurements collected from different fingers. The results in Figure 10 show that the true values and predicted values are mostly distributed along a linear line for all positions, especially in position-1 (little finger), indicating accurate hand-grip strength estimation for HIPPO.

Table 6. Root mean square error RMSE (unit kg) and $R^2$ score of predicting hand-grip strength (HS) in different experimental conditions. Model data → Predicted. Regression Method: Automatic Relevance Determination Regression (ARD), Ridge Regression (Ridge). Features: light reflectivity change (L), gender (G) and hand size (S), age (A).

| Test conditions | Position-1 | | | | | | Position-2 | | | | | | Position-3 | | | | | | Overall | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ARD | | Ridge | | Average | | ARD | | Ridge | | Average | | ARD | | Ridge | | Average | | Average | |
| | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ |
| **(L) → HS** | 9.63 | 0.02 | 9.49 | 0.05 | 9.56 | 0.04 | 10.08 | -0.07 | 9.70 | 0.01 | 9.89 | -0.03 | 9.84 | -0.02 | 9.59 | 0.03 | 9.72 | 0.01 | 9.72 | 0.01 |
| **(L,S) → HS** | 5.42 | 0.69 | 5.38 | 0.70 | 5.40 | 0.70 | 6.45 | 0.56 | 6.49 | 0.56 | 6.47 | 0.56 | 6.10 | 0.61 | 5.90 | 0.63 | 6.00 | 0.62 | 5.96 | 0.63 |
| **(L,G) → HS** | 3.33 | 0.88 | 3.32 | 0.88 | 3.33 | 0.88 | 5.98 | 0.62 | 6.14 | 0.60 | 6.06 | 0.61 | 4.80 | 0.76 | 4.75 | 0.76 | 4.78 | 0.76 | 4.72 | 0.75 |
| **(L,S,G) → HS** | 2.58 | 0.93 | 2.56 | 0.93 | 2.57 | 0.93 | 5.42 | 0.69 | 5.42 | 0.69 | 5.42 | 0.69 | 4.51 | 0.79 | 4.29 | 0.81 | 4.40 | 0.80 | 4.13 | 0.81 |
| **(L,S,G,A) → HS** | 2.55 | 0.93 | 2.68 | 0.93 | 2.62 | 0.93 | 5.42 | 0.69 | 5.62 | 0.67 | 5.52 | 0.68 | 4.44 | 0.79 | 4.50 | 0.79 | 4.47 | 0.79 | 4.20 | 0.80 |

## 7 PRACTICALITY: SMART RING EXPERIMENTS

The results thus far have demonstrated that light sensors located on fingers can be used to estimate hand-grip strength. We also showed that the results vary across different fingers and individuals, with the best results requiring to use multiple contact points and background information about the user's gender. As the smart glove can constrain the hand-grip of some participants, we next demonstrate that our solution is feasible also in more practical scenarios by presenting an optimized design of the HIPPO wearable, and carrying out further experiments using everyday household objects and $N = 14$ participants. These experiments were designed to




(a) Position-1 (b) Position-2 (c) Position-3

Fig. 10. Hand-grip strength estimation performance in different positions.

show that HIPPO can indeed piggyback interactions with everyday objects to obtain continuous estimates of grip strength. We also consider a wider variety of experimental conditions and new situations that can influence the estimations of hand-grip strength though HIPPO.

## 7.1 Experimental Design

*7.1.1 Everyday Objects.* As household objects used in our experiments, we rely on a (A) disposable cup (Poly-Coated paper), (B) plastic cup (PET), (C) kitchen sponge (Microfiber), (D) Paper-sheet (Wood fibres), (E) Fleece jacket (Polyester), (F) Face mask (Polypropylene - PP), (G) Plastic bag (HDPE), (H) Beer can (Aluminum) and (I) Metallic scrubbers (Stainless steel) (see Figure 11(b)). The first three objects were evaluated by all participants, whereas objects (D) - (I) were only sampled by a single participant (6 trials per object). Limiting the number of objects that were interacted with was necessary to maintain the length of the study feasible for participants.

*7.1.2 Participants.* 14 participants were recruited (Males=7, Females=7). The participants were university students, staff and also the researcher's social circle from different fields and nationalities. Their average age was $23.93 \pm 5.01$ and all of them were right-handed.

*7.1.3 Wearable Prototype.* We built an optimized smart ring prototype that embeds the light sensors to a ring and connects to a computing board for carrying out the analysis of values. Figure 11(a) shows the prototype which is worn by an individual in the right hand and located in the ring finger (light sensor in position-1). The prototype uses a wireless M5StickC PLUS ESP32 development board that controls the sampling frequency of the light sensor and uploads the samples to a centralized server. The M5StickC Plus contains an inbuilt Wi-Fi connection facility, battery supplies (120 mAh @ 3.7V) and LCD screen to externalize the activities of the board. Moreover, it is lightweight (21g) and portable, such that it can be placed in a wristband ($65 * 25 * 15$mm). The M5StickC PLUS reads photo resistor's values through G36 pin and can show the light reflectivity values on its screen in real time. The board externalizes a light sensor through a dedicated and isolated wire that is attached to a plastic ring. The ring is a ready-made manufactured product, whose shape is flexible as its core is made from an elastic wire. We used the same type of red laser diode (650nm 5mW $3 - 5$V) and a photo-resistor (5M$\Omega$) as in our smart glove prototype. Since the shape of ring is flexible, it is easy to adjust to different finger characteristics.


(a) (b)

Fig. 11. Common house hold objects used in the wild experiment: a) optimized HIPPO wearable that consists in a wristband and a ring; b) (1) first set: A) disposable cup, B) plastic cup, C) kitchen sponge; b) (2) second set: D) paper-sheet, E) fleece jacket, F) face mask, G) plastic bag, H) beer can, I) metallic scrubbers.

*7.1.4 Procedure.* Experiments we carried follow the same standard procedure as when using the dynamometer (See details in Section 6. As in previous experiments, the researcher conducting the experiment explained the overall procedure and collected a signed informed consent form from every participant. The experiment was encoded into a $1 \times 2$ factorial design with the object type and trial as independent variables, following the design of our controlled experiment. To eliminate order effect and biases, whilst keeping the number of trials manageable, trial number was counterbalanced following a Latin Square design, resulting in eight experimental conditions: (1) Trial1-DYNA, (2) Trial2-DYNA, (3) Trial1-A, (4) Trial2-A, (5) Trial1-B, (6) Trial2-B, (7) Trial1-C and (8) Trial2-C (A, B and C are the 3 objects for the experiment). The duration of the experiment was around 25 minutes. In addition to this, the researcher collected 6 trials worth of measurements for the other objects (D)-(I). The evaluation took place in the same university room as the other experiments (see Section 6).

## 7.2 Results

*7.2.1 Characteristics of Light Intensity.* Figure 12(a) shows a characterization of the light reflectivity values for the different objects across all participants. The mean light values vary across different objects and the variance in the light measurements for each object is low: disposable cup (Mean=2431.18, SD=59.26), plastic cup (Mean=3172.54, SD=45.94) and kitchen sponge (Mean=3266.34, SD=59.09). The variation in the measurements is mostly caused by small motions, but overall the effect is negligible. The effect of these motions can be mitigated by integrating a motion sensor that detects periods where the hand is stable and only considering those periods. Figure 12(b) illustrates this point, showing how the variance in measurements is significantly reduced when only stable periods are considered for measurements. Finally, Figure 12(c) compares the light values across different objects and across all the participants. The values vary across objects, which simply shows that the changes in intensity depend on the surface characteristics of the objects. As HIPPO uses relative changes in light intensity between minimum and maximum grip force, this does not affect the hand-grip strength estimates. However, the result shows that interactions with *different* objects can be identified from the light intensity values.

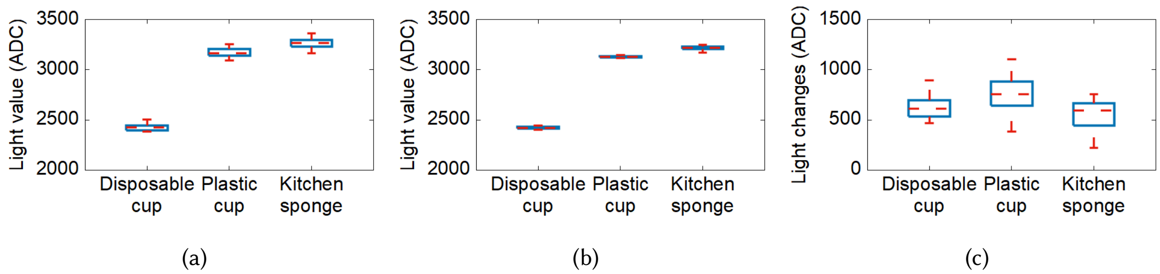


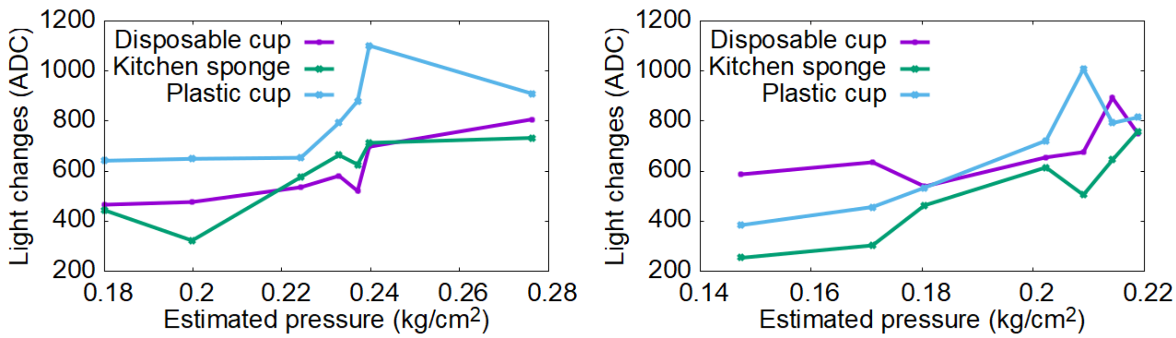

Fig. 12. Capturing hand-grip strength, a) Variations in light values of the objects across all participants (in the relaxed state), b) Light characterization of the objects (in the relaxed state), c) Quantification of hand-grip strength in different objects across all participants.

*7.2.2 Validity.* We verified that our new wearable design captures representative data of hand grip strength by comparing the collected light measurements against the gold standard (dynamometer). Table 7 shows the results of Kolmogorov-Smirnov test on pairs of data. No statistically significant differences are found, i.e., the *changes* in light intensity values reflect the actual force-grip strength. We also separately compare the similarity of the changes in light intensity values with the estimated pressure applied on the object, i.e., the force given by the dynamometer divided by the approximate hand surface area size. The similarity with pressure values is slightly higher than with the dynamometer values, especially for female participants. Thus, similarly to the controlled experiments, the fit between the sensor and the object have slight influence on the intensity values but overall the results are sufficiently stable across participants to estimate hand grip strength. Figure 13 also indicates that there is a strong correlation between the light reflectivity changes and DYNA-hand in different objects for males and females. From Table 7, we can also observe that despite the different mechanical properties of the objects, the generality of our approach across different objects is well-suited for different participants.

Table 7. Data similarity ($p-$value) between light reflectivity changes in the object and two measures: DYNA (dynamometer value), DYNA-hand (estimated pressure on the object, calculated by dividing the dynamometer reading (force) with the hand size).

| Similarity Analysis | Disposable cup | | | Plastic cup | | | Kitchen sponge | | |
|---|---|---|---|---|---|---|---|---|---|
| | Male | Female | All | Male | Female | All | Male | Female | All |
| **DYNA** | 0.962 | 0.937 | 0.904 | 0.962 | 0.937 | 0.998 | 0.962 | 0.937 | 0.904 |
| **DYNA-hand** | 0.962 | 0.962 | 0.920 | 0.962 | 0.962 | 0.999 | 0.962 | 1 | 0.999 |

*7.2.3 Performance.* We evaluate HIPPO performance by using the same regression and classification models as before to predict exact hand-grip strength (10-fold cross validation) and strength category (5-fold cross validation). We report the average accuracy across all tests. In this experiment, participants scored all types (weak, normal and strong) of hand-grip strength. We also trained the model on individual objects to test the classification sensitivity of different objects. From the smart glove experiment, the best performance of estimated hand-grip strength is achieved by the combination of the light change, hand size and gender. Therefore, we consider this combination for our field (i.e., in the wild) evaluation. We still consider age as an input parameter due to the relevance between




(a) Male participants (b) Female participants

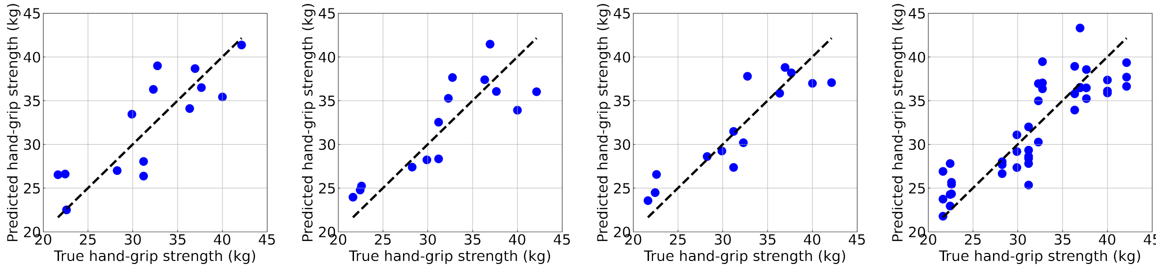
Fig. 13. Estimated pressure on the object (DYNA-hand) captured by the light senor in different objects.

age and strength type according to the dynamometer norm table. Table 8 shows the classification accuracy of HIPPO on the individual object as well as all objects in different conditions. We can observe that plastic cup and kitchen sponge (both 73.3%) performed better than a disposable cup (71.7%). Since squeezing the disposable cup is harder than squeezing the plastic cup and sponge, the variation in light changes using the disposable cup across the participants is lower, which might lead to a low accuracy. The performance of the individual object can be further improved if more samples are obtained from each object since most hand grips are of the normal category in the experiment. The accuracy increased greatly up to 90.6% when training the models on all objects. Therefore, a better hand-grip strength type estimation can be achieved with the combined measurements from different daily objects. Moreover, when we consider the object type as one of the parameters and train the model on all objects, The best performance can be achieved with the accuracy 91.9% (RF 90.6% and GB 93.1%), a slight increase compared to the performance on all objects without considering object types. This further proves that although different mechanical properties of the objects might result in different patterns of light reflectivity, their performance of strength type estimation is almost consistent. Figure 14 also shows that accuracy is good since the predicted and true values closely align with a straight line centered in the origin.

Table 8. Evaluation on regression (RMSE kg, $R^2$ score) of predicting hand-grip strength (HS) and classification accuracy(%) of predicting hand-grip strength type (ST) in different conditions. Features: light reflectivity change (L), gender (G), hand size (S), age (A) and object (O).

| **Test conditions** | **Object** | **Regression** | | **Classification(%)** |
|---|---|---|---|---|
| | | **RMSE** | $R^2$ | |
| **(L,S,G,A)** | **Disposable cup** | 3.54 | 0.68 | 71.7 |
| | **Plastic cup** | 3.44 | 0.70 | 73.3 |
| | **Kitchen Sponge** | 2.96 | 0.78 | 73.3 |
| | **All objects** | 3.20 | 0.75 | 90.6 |
| **(L,S,G,A,O)** | **All objects** | 3.22 | 0.74 | 91.9 |

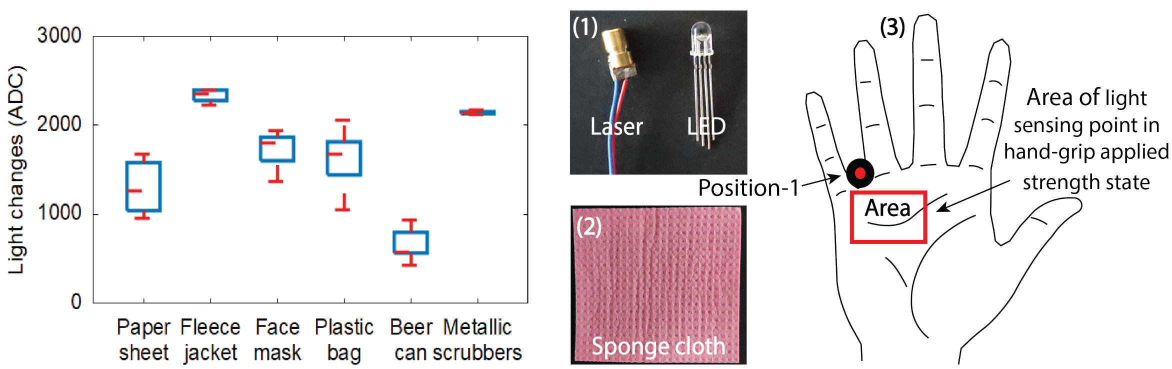
*7.2.4 Other Household Objects.* Figure 15(a) shows the light sensor values of the additional household objects (i.e., (D) - (I)) that were sampled six times by the researcher. In line with the other results, each individual object has a unique light fingerprint despite the force being (approximately) constant. The fingerprints also have low




(a) Disposable cup (b) Plastic cup (c) Kitchen sponge (d) All objects

Fig. 14. hand-grip strength estimation performance of different objects.

overall variance: paper sheet (Mean=1298.21, SD=302.60), fleece jacket (Mean=2452.42, SD=47.92), face mask (Mean=1731.34, SD=211.65), plastic bag (Mean=1621.75, SD=352.26), beer can (Mean=645.63, SD=185.85), metallic scrubbers (Mean=2145.54, SD=17.62). Overall the variance is somewhat higher for some of the objects. This mainly concerns objects that are hard to grab (paper sheet) or that have a shiny (beer can) or translucent surface (plastic bag). Taken together, the results show that HIPPO is practical and can operate robustly across users and everyday household objects. Some objects are better suited for HIPPO than others, but these can be identified by examining the distribution and changes in light intensity values.




(a) (b)

Fig. 15. a) The changes in light intensity values for the additional household objects, b) evaluation of other factors on HIPPO: (1) Laser vs LED, (2) Unseen (new) object and (3) Sensing without objects

## 7.3 Impact of Design and Environmental Factors on HIPPO

HIPPO has been designed as a solution that can operate as part of everyday interactions instead of requiring a dedicated measurement protocol, unlike existing solutions. We next briefly assess the effects of different environmental and other design factors on the performance of HIPPO to demonstrate that the hand-grip estimates are robust across a wide range of factors. These tests were carried out through separate experiments conducted independently and in a small scale setting with additional participants. The main reason for this is to avoid having longer experiments, which are not engaging to participants and can potentially be noisy, and also to avoid the experiments from becoming a burden for participants. Moreover, it is not possible to obtain consistent hand-grip measurements from consecutive measurements that require applying heavy force. We recruited 6 participants (age 31.83 ± 9.70), three males and three females, to have a balanced distribution (participants 1-3 are females). The procedure to collect hand-grip measurements remains the same as in previous experiments (see details in Section 6). The duration of the experiment was on average 30 minutes. These experiments are conducted using the same smart ring prototype as described previously (laser as the light source).

*7.3.1 Effect of the Luminosity.* Since environmental conditions can influence light values, we have also evaluated the impact of environmental luminosity considering three conditions: indoor dark (Dark), indoor ambient light (IAL) and outdoor ambient light (OAL). The indoor ambient light condition is the same as in the previous experiment. Measurements were collected for 7-days for laser and LED independently. Plastic cup and kitchen sponge (See B and C in Figure 11(b)) were used as the household objects in this experiment. Figure 16 shows the luminosity (LUX) of the measurements in the different environments. The luminosity is stable in the two indoor environments, whereas the ambient light contains more variations in the outdoor case. Luminosity shows to be constant during both laser and LED experiments.

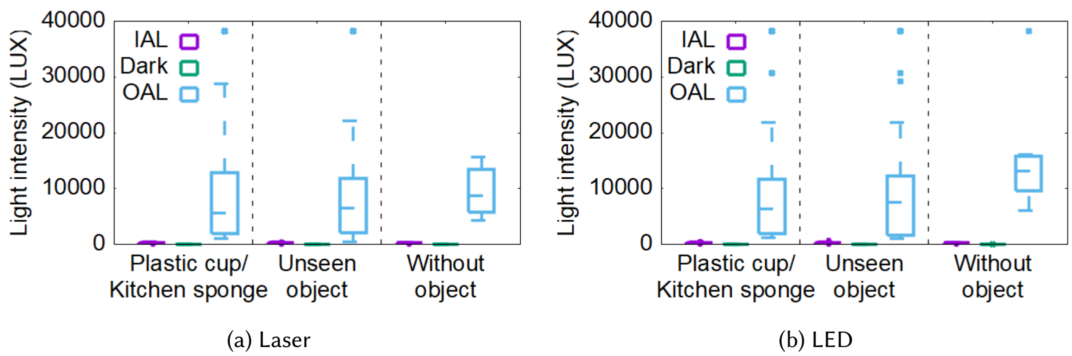
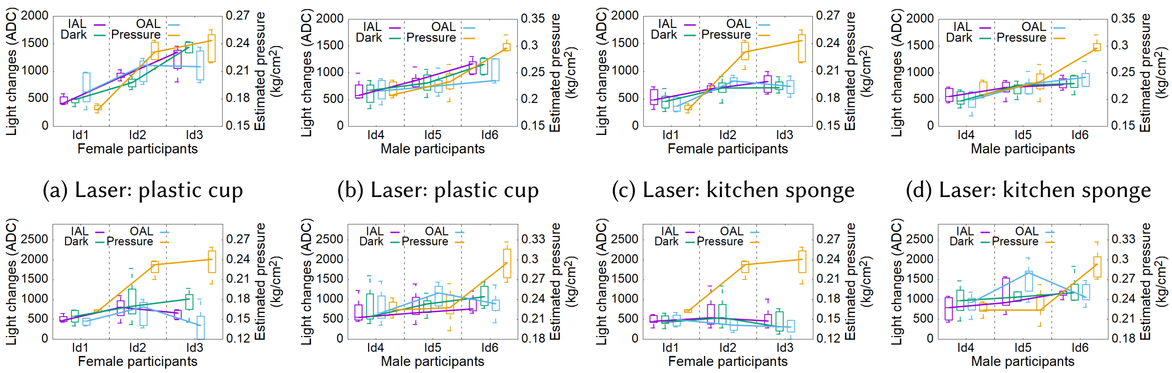



Fig. 16. Light intensity (LUX) in different experimental environments (IAL: indoor ambient light, Dark: indoor dark, OAL: outdoor ambient light).

Figure 17(a-d) shows the results of estimated pressure (DYNA-hand) and their respective light values in the different luminosity environments. We also separated the results by gender as hand size and finger positions play an important role, as we showed previously. From the figure, we can observe that light changes can estimate relatively similar pressure in all the environments. We also repeat the regression experiments by re-training our models using the measurements from the 7-days. Training and testing are carried out using leave-one-day-out cross validation. Table 9 shows the laser results of HIPPO using RMSE and $R^2$ values. The accuracy is consistently high, with the two indoor environments resulting in the best performance. Thus, luminosity impacts the results due to largest variations in ambient sunlight, but this is generally negligible. The regression results in Figure 18 (a-d) similarly show high accuracy, and the average classification performance for hand-grip strength type is 90.87% (IAL: average 93.44%, Dark: average 92.26%, OAL: average 88.69% and All: average 90.87%) in the different environments from Figure 19(c).

*7.3.2 Effect of Light Source.* We also assessed whether the laser could be replaced by a LED (red-color, 5 mm in size, 0.06W power draw, and luminous intensity of 1500 mcd at a 30° angle) shown in Figure 15(b)(1). The laser produces monochromatic and heavily directed light, whereas the spectrum of light produced by the LED contains more variation. The results in Figure 17(e-h) show that no clear relationship can be established between light




(a) Laser: plastic cup (b) Laser: plastic cup (c) Laser: kitchen sponge (d) Laser: kitchen sponge

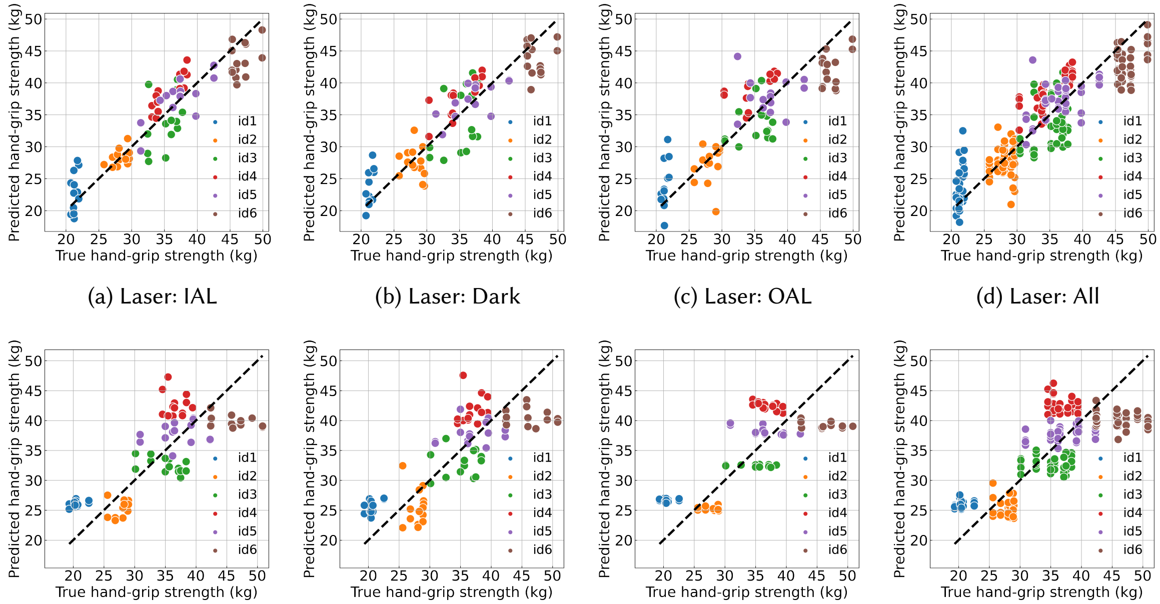
(e) LED: plastic cup (f) LED: plastic cup (g) LED: kitchen sponge (h) LED: kitchen sponge

Fig. 17. Estimated pressure (DYNA-hand) captured by light reflectivity changes through 7-day measurements in different environments: IAL-indoor ambient light, Dark-indoor dark, OAL-outdoor ambient light.

Table 9. Root mean square error RMSE (kg) and $R^2$ score of predicting hand-grip strength (HS) in different environments. Features: light reflectivity change (L), gender (G) and hand size (S), age (A), object (O), light conditions LUX (C).

| Sensors | Test conditons | | Measure-1 | | Measure-2 | | Measure-3 | | Measure-4 | | Measure-5 | | Measure-6 | | Measure-7 | | 10-CV | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ |
| **Laser** | **IAL** | **(L,S,G,A,O)** | 2.64 | 0.87 | 3.47 | 0.80 | 3.60 | 0.79 | 2.59 | 0.89 | 2.62 | 0.89 | 3.19 | 0.87 | 3.03 | 0.89 | 3.13 | 0.85 |
| | | **(L,S,G,A,O,C)** | 2.64 | 0.87 | 3.47 | 0.80 | 3.60 | 0.79 | 2.59 | 0.89 | 2.62 | 0.89 | 3.19 | 0.87 | 3.03 | 0.89 | 3.14 | 0.85 |
| | **Dark** | **(L,S,G,A,O)** | 3.60 | 0.76 | 2.66 | 0.88 | 3.73 | 0.78 | 2.85 | 0.86 | 3.33 | 0.81 | 3.52 | 0.85 | 3.74 | 0.82 | 3.47 | 0.82 |
| | | **(L,S,G,A,O,C)** | 3.60 | 0.76 | 2.66 | 0.88 | 3.73 | 0.78 | 2.85 | 0.86 | 3.33 | 0.81 | 3.52 | 0.85 | 3.74 | 0.82 | 3.47 | 0.82 |
| | **OAL** | **(L,S,G,A,O)** | 4.77 | 0.59 | 4.42 | 0.68 | 4.08 | 0.73 | 3.70 | 0.77 | 3.40 | 0.80 | 4.42 | 0.76 | 4.04 | 0.79 | 4.19 | 0.74 |
| | | **(L,S,G,A,O,C)** | 4.78 | 0.58 | 4.46 | 0.67 | 4.08 | 0.73 | 3.70 | 0.77 | 3.45 | 0.80 | 4.68 | 0.73 | 4.04 | 0.79 | 4.23 | 0.73 |
| | **All** | **(L,S,G,A,O)** | 3.70 | 0.75 | 3.51 | 0.80 | 3.78 | 0.77 | 3.16 | 0.83 | 3.28 | 0.82 | 3.93 | 0.81 | 3.58 | 0.84 | 3.54 | 0.81 |
| | | **(L,S,G,A,O,C)** | 3.70 | 0.75 | 3.51 | 0.80 | 3.78 | 0.77 | 3.16 | 0.83 | 3.28 | 0.82 | 3.99 | 0.80 | 3.58 | 0.84 | 3.56 | 0.81 |
| **LED** | **IAL** | **(L,S,G,A,O)** | 5.38 | 0.36 | 4.28 | 0.74 | 6.15 | 0.56 | 4.48 | 0.63 | 4.92 | 0.54 | 5.35 | 0.69 | 4.32 | 0.77 | 5.24 | 0.61 |
| | | **(L,S,G,A,O,C)** | 5.34 | 0.37 | 4.53 | 0.70 | 6.08 | 0.57 | 4.40 | 0.64 | 4.85 | 0.55 | 5.56 | 0.67 | 4.38 | 0.77 | 5.24 | 0.61 |
| | **Dark** | **(L,S,G,A,O)** | 5.48 | 0.34 | 4.40 | 0.72 | 5.61 | 0.63 | 3.50 | 0.77 | 4.01 | 0.69 | 5.08 | 0.72 | 5.04 | 0.69 | 4.94 | 0.65 |
| | | **(L,S,G,A,O,C)** | 5.50 | 0.33 | 4.39 | 0.72 | 5.61 | 0.63 | 3.69 | 0.75 | 4.03 | 0.69 | 5.11 | 0.72 | 5.10 | 0.68 | 4.94 | 0.65 |
| | **OAL** | **(L,S,G,A,O)** | 5.82 | 0.25 | 4.55 | 0.70 | 6.11 | 0.56 | 4.88 | 0.56 | 5.15 | 0.49 | 5.55 | 0.67 | 4.54 | 0.75 | 5.39 | 0.59 |
| | | **(L,S,G,A,O,C)** | 5.83 | 0.25 | 4.54 | 0.70 | 6.19 | 0.55 | 4.86 | 0.56 | 5.16 | 0.49 | 5.88 | 0.63 | 4.53 | 0.75 | 5.41 | 0.59 |
| | **All** | **(L,S,G,A,O)** | 5.69 | 0.28 | 4.42 | 0.72 | 5.94 | 0.59 | 4.25 | 0.67 | 4.94 | 0.54 | 5.30 | 0.70 | 4.54 | 0.75 | 4.98 | 0.65 |
| | | **(L,S,G,A,O,C)** | 5.69 | 0.28 | 4.42 | 0.72 | 5.95 | 0.59 | 4.25 | 0.67 | 4.95 | 0.53 | 5.35 | 0.69 | 4.54 | 0.75 | 4.99 | 0.65 |

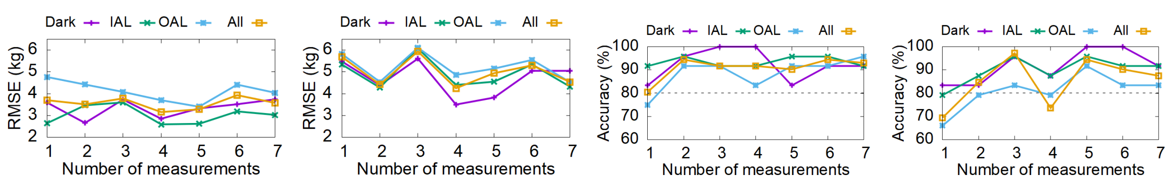
changes and the estimated pressure (DYNA-hand) as given by the dynamometer. This is a direct consequence of the variations in the light spectrum of the LED and in practice this mostly affects the regression estimates and cases where the strength values are close to the border between two categories. Indeed, the laser consistently outperforms the LED source, even if the LED can also be used to obtain insights about hand-grip strength. Specifically, HIPPO combined with laser performs better than LED in regression from Table 9 (laser: average RMSE= 3.56 kg, and LED: average RMSE=5.01 kg), as well as in classifying the hand-grip strength category (IAL: average 91.66%, Dark: average 89.82%, OAL: average 80.85% and All: average 85.31%). We also notice from Figure 19 (d) that the performance of LED is not consistent during different days (OAL) and the accuracy is below 80%




(a) Laser: IAL (b) Laser: Dark (c) Laser: OAL (d) Laser: All

(e) LED: IAL (f) LED: Dark (g) LED: OAL (h) LED: All

Fig. 18. Hand-grip strength estimation performance by 10-fold cross validation across 7-day measurements in different environments.




(a) Laser (b) LED (c) Laser (d) LED

Fig. 19. Evaluations on hand-grip strength estimation (RMSE) and strength type classification(%) across 7-day measurements in different environments.

for 3 out of 7-day measurements. Figure 18 (e-h) also show estimation performance by 10-fold cross validation, which we find to be less accurate along $y = x$ with LED, especially in outdoor ambient environments.

*7.3.3 Unseen Household Objects.* Ultimately HIPPO should operate on any everyday interactions without having to rely on models tailored for specific objects. We tested performance for a previously unseen object by introducing an object made of sponge cloth (cellulose with cotton) shown in Figure 15(b)(2). We train the models with the data from the two objects described above (plastic cup and kitchen sponge) and test against the data from the cloth. The data of the cloth was also collected across 7-day measurements from the same 6 participants as the plastic cup and kitchen sponge. The results in Figure 20 show the trend between light changes and estimated pressure to be similar, and robust across gender, and environment. Table 10 shows the regression and classification performance,

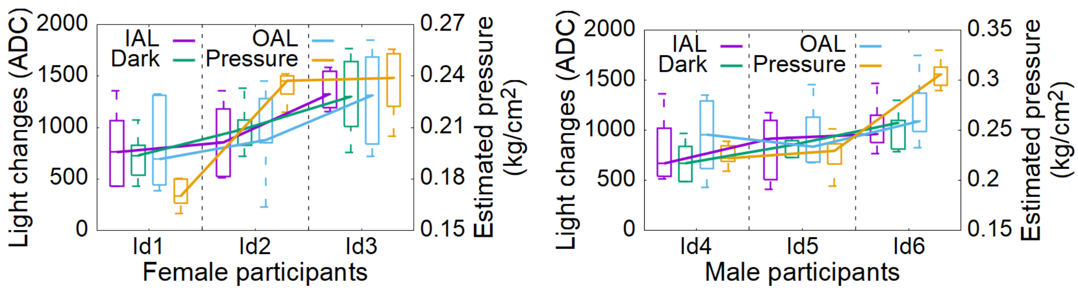


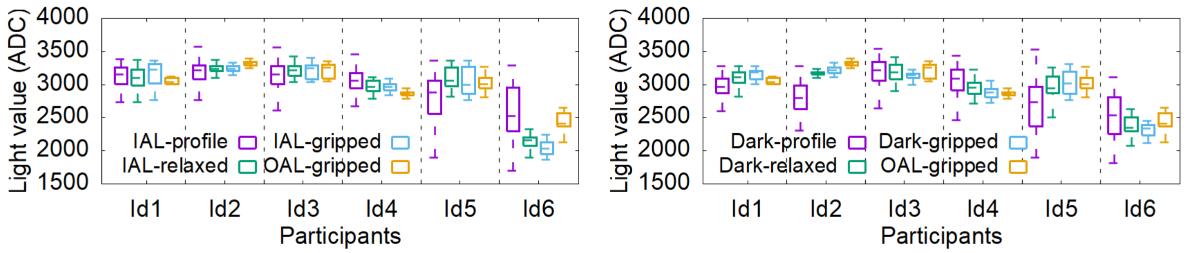

Fig. 20. Estimated pressure (DYNA-hand) captured by light reflectivity changes on unseen (new) object through 7-day measurements in different environments.

Table 10. Unseen object evaluations on hand grip strength estimation RMSE (kg) and strength type classification (%) in different environments.

| Test conditions | Regression RMSE | Classification(%) | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | Id1 | Id2 | Id3 | Id4 | Id5 | Id6 | All Ids |
| **IAL** | 5.45 | 71.43 | 85.71 | 100 | 71.43 | 78.57 | 100 | **83.33** |
| **Dark** | 4.91 | 71.43 | 100 | 100 | 71.43 | 100 | 100 | **90.47** |
| **OAL** | 4.84 | 85.71 | 85.71 | 100 | 85.71 | 100 | 100 | **92.86** |
| **All** | 5.05 | 85.71 | 90.48 | 100 | 69.04 | 100 | 100 | **90.88** |

which remain reasonably high despite variations across individuals (IAL 83.33%, Dark 90.47 and OAL 92.86% and All 90.88%). For two users (1 and 4, female and male), the drop in performance was more significant (1: 71.43%, 4: 71.43%), which resulted from low similarity between the light values considered for training and testing. The sponge cloth is easiest to squeeze and thus it should result in highest variation and deformations. The two users whose estimates were least accurate both had low pressure grips, resulting in a small number of deformations and making the light intensity values relatively stable. Thus, the performance with unseen objects depends on the characteristics of the object and may also depend on the grip-strength category of the individual as the presence or absence of deformations may impact how well prior data fits the user.

*7.3.4 Performance without Object.* Hand-grip strength estimates should only be calculated when the user is interacting with an object, and thus there is a risk of false positives if the user clenches their fist or keeps the hand open without exerting a pressure. As final step, we investigate whether these cases can be reliably detected and omitted from analysis. We perform this from the same participants by examining the light intensity values when the user's hand is clenched (or gripped) or open without interacting with an object. Figure 21 shows the resulting light values and the light values in the flat (or relaxed) state are from the area shown in Figure 15(b)(3). The light values are similar for the same individual, and we can observe similarities between the relaxed and clenched (gripped) states. This indicates that when there is a hand-grip, the sensors read the same information no matter the environment. Table 11 shows the mean and standard deviation of the light intensity values, showing small variations between the relaxed and the clenched states. These values are significantly different from those when the user interacts with an object, and thus interactions with objects can be detected by identifying sudden significant changes in the light intensity values. This suggests that false positives can be significantly mitigated. Another implication of this result is that it offers potential for resource savings by helping to identify when measurements need to be processed.




(a) IAL+OAL

(b) Dark+OAL

Fig. 21. Light values of hand with different states in different environments: profile - light profile of the whole hand in the flat state, gripped - light values in the hand-grip applied strength state, relaxed - light values in the flat state where the sampling area is based on the area of the sensing point in gripped state. The same OAL-gripped values shown with both IAL and Dark environments.

Table 11. Light values (ADC) without objects in different environments: profile - light profile of the whole hand in the flat state, gripped - light values in the hand-grip applied strength state, relaxed - light values in the flat state where the sampling area is based on the area of the sensing point in gripped state.

| Participants | IAL | | | Dark | | | OAL |
|---|---|---|---|---|---|---|---|
| | Profile | Relaxed | Gripped | Profile | Relaxed | Gripped | Gripped |
| **Id1** | 3124.66±160.07 | **3098.57±160.16** | **3160.73±169.46** | 2967.15±161.50 | **3099.02±105.23** | **3152.84±77.16** | **3050.94±42.99** |
| **Id2** | 3166.21±185.28 | **3232.78±54.23** | **3239.79±45.64** | 2823.02±267.93 | **3168.97±44.06** | **3322.69±40.39** | **3322.69±40.39** |
| **Id3** | 3132.75±188.94 | **3212.64±96.54** | **3217.71±109.55** | 3169.31±201.13 | **3186.00±133.89** | **3128.87±67.21** | **3217.70±109.55** |
| **Id4** | 3055.49±155.59 | **2972.56±81.71** | **2960.00±61.37** | 3064.16±119.11 | **2944.32±104.08** | **2873.54±82.57** | **2877.44±66.09** |
| **Id5** | 2792.64±362.54 | **3086.82±153.19** | **3058.77±204.64** | 2697.65±394.11 | **2982.57±172.06** | **3020.08±181.59** | **3015.21±105.84** |
| **Id6** | 2607.17±395.79 | **2121.34±117.20** | **2042.92±110.74** | 2521.258±325.29 | **2383.64±156.06** | **2308.92±105.36** | **2431.00±150.99** |

## 8 DISCUSSION

**Factors that influence hand-grip strength:** Age and gender are factors that influence hand-grip measurements, and there are very well defined index values associated with them. The average grip strength is 46kg for men and 29kg for women [35]. In our work, we demonstrated that our light sensing approach can also capture this strength as the results preserve the relative patterns measured by a certified dynamometer.

**Room for improvement:** We demonstrated in our work that hand-grip strength can be estimated using light sensors located in a smart glove prototype. As software and hardware of light sensors are already miniaturized, e.g., smartwatches, the deployment of our approach can be optimally envisioned within smart rings. Indeed, existing commercial solutions either implement light sensors (that can be re-purposed) or could be easily extended with light sensors to introduce our approach transparently into daily routines of users. The performance of HIPPO showed highly promising performance, correlating well with a clinical baseline (dynamometer), but naturally there is further work to improve the robustness of the estimates and to support interactions with a wider range of household objects. We are also interested in generalizing our approach into a larger spectrum of interactions with household objects, and different body positions.

**Daily hand-grip monitoring:** Previous work has reported that the body position that is used for measuring hand-grip strength can influence the results of the overall measurements [11]. However, it is also noticed by these studies that to overcome this problem, the strength values just have to be adjusted based on the body position, such that those can be interpreted fairly. In addition, it has also been found that just 4 kg of hand-grip strength is required to perform 90% of daily living activities (ADL) [24]. Thus, there are opportunities to measure hand-grip strength directly from interactions or indirectly by asking the user. As part of the post questionnaire for each participant in our main experiment, we asked whether they have used dynamometer before to measure their hand-grip strength. Overall 62% of the participants mentioned that they did not use it before. We also asked whether they would be interested on acquiring a dynamometer in the future to measure their hand-grip continuously at home. Overall 83.3% of participants mentioned that they are not interested. All in all, this highlights further the need of non-intrusive approaches for measuring health based on hand-grip indicators.

**Other light spectrum:** We demonstrated that light sensing in the red spectrum can be used to capture hand-grip strength measurements. By looking at the reflective patterns of the changing surface of the object as the hand squeezes the object, it is possible to extrapolate the intensity of the hand-grip. Other spectrum of light can also be re-purposed to achieve this, e.g., blue and green, we are interested in investigating its performance as some spectrums are preferable over others based on the context of the user. For instance, red light would be suitable underwater when compared with blue light.

**Comparison to other sensing modalities:** While pressure sensors can be used as an alternative sensing modality to measure hand-grip strength, its deployment is rather difficult as its placement within the hand plays an important role to obtain accurate measurements. Thus, it is difficult to introduce it in a transparent manner to users. In our work, an additional pressure sensor is located in the (hand) palm and we found high variance in the results when measuring hand-grip of squeezing objects. One reason of this is that soft materials tend to absorb the grip force so that the sensor is not able to detect and distinguish it. For instance, a rubber ball will absorb most of the force from the hand-grip.

**End-user adoption:** The results demonstrate that a simple light sensor embedded in a ring can be used to estimate the hand grip strength of an individual, and to provide insights into changes in the user's health. Naturally further optimizations would be required in practice. Firstly, most wearable devices are combined with a compendium application that runs on a smartphone. HIPPO could similarly benefit from such design, offloading the analysis of the light intensity values onto the smartphone instead of performing them on the ring. The smartphone application can also be used to obtain information that supports the analysis, e.g., hand size parameters could potentially be estimated on the smartphone from touch screen interaction patterns. The sampling on the ring can also be further optimized using a proximity sensor to detect when the user is interacting with objects.

**Inherent object characteristics :** Surface deformations are dependent on inherent characteristics of the material of the object being interacted with and these variations can affect the light intensity measurements captured by HIPPO. For example, hard surfaces (such as the wooden ball used as the baseline) might not alter their shape, whereas malleable objects can undergo significant surface changes. In both cases, the light intensity values change as force is applied, but the patterns of changes vary depending on the surface of the object. Further improving the robustness of the estimates may require averaging estimates from multiple interactions and potentially from different objects. Alternatively, it may be possible to suggest activities to create opportunistic moments for hand-grip estimation, e.g., by inducing interactions on a smartphone by providing recommendations.

**Application scenarios:** HIPPO presents an important first step toward harnessing everyday interactions for deriving health related information. While the main focus in this paper has been on interactions with everyday objects, HIPPO is also beneficial to more specialized domains. For example, hospitals or care homes could give medical rings to patients and use HIPPO to continuously estimate hand grip instead of requiring separate test assessments.

**Practicability:** Optimally, we envision HIPPO to be integrated into smart rings, which already contain the required sensor, re-purposing these devices for hand-grip estimation. The light sensors used by HIPPO are low-cost, low-power, and small in size, making it reasonably easy to integrate HIPPO with diverse wearables. Indeed, wearables already use light sensors for measuring heart rate and other physiological parameters, and

HIPPO uses similar technology but is placed on the exterior of the wearable to derive hand grip information. Our experiments showed that it is possible to detect when objects are held and this information can be used to optimize resource consumption.

## 9 SUMMARY AND CONCLUSIONS

We contributed HIPPO, an innovative sensing solution and a new sensing modality for assessing hand-grip strength from opportunistic interactions with everyday objects. HIPPO captures hand-grip estimations by looking at changes in the surface of objects using light sensors. Through extensive experiments that considered a wide range of everyday objects and 44 participants, we demonstrated that HIPPO can capture hand-grip estimations that align with a clinically certified dynamometer. We also compared our proposed method against other state-of-the-art baselines, demonstrating that HIPPO can capture pressure-based estimations through light and provide an easy-to-use and natural alternative that harnesses everyday interactions. The best results are obtained when there are multiple measurement points per individual, i.e., when multiple interactions with different objects are piggybacked. The results also showed some interactions being better for estimation as others as the contact between the light sensor and the object needs to be sufficiently good to capture the changes in shape. Our method paves the way toward non-intrusive solutions for capturing individual's hand-grip strength – an important health-related parameter – continuously and pervasively.

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## REFERENCES

[1] Diane E Adamo, Tara Anderson, Mahtab Koochaki, and Nora E Fritz. 2020. Declines in grip strength may indicate early changes in cognition in healthy middle-aged adults. *PloS One* 15, 4 (2020), e0232021. https://doi.org/10.1371/journal.pone.0232021

[2] Williams A. Andrews and Richard W Bohannon. 2000. Distribution of muscle strength impairments following stroke. *Clinical Rehabilitation* 14, 1 (2000), 79–87. https://doi.org/10.1191/026921500673950113

[3] Pablo Arias, Christopher Kelley, Janelle Mason, Kelvin Bryant, and Kaushik Roy. 2018. Classification of user movement data. In *Proceedings of the International Conference on Digital Signal Processing*. ACM, Tokyo, Japan, 156–160. https://doi.org/10.1145/3193025.3193036

[4] Bert Arnrich, Oscar Mayora, Jakob Bardram, and Gerhard Tröster. 2010. Pervasive healthcare. *Methods of Information in Medicine* 49, 01 (2010), 67–73. https://doi.org/10.3414/ME09-02-0044

[5] Johannes Beller, Alexander Miething, Enrique Regidor, Lourdes Lostao, Jelena Epping, and Siegfried Geyer. 2019. Trends in grip strength: Age, period, and cohort effects on grip strength in older adults from Germany, Sweden, and Spain. *SSM-Population Health* 9 (2019), 100456. https://doi.org/10.1016/j.ssmph.2019.100456

[6] Richard W Bohannon. 2019. Grip strength: An indispensable biomarker for older adults. *Clinical Interventions in Aging* 14 (2019), 1681. https://doi.org/10.2147%2FCIA.S194543

[7] Richard W Bohannon and Karen L Schaubert. 2005. Test–retest reliability of grip-strength measures obtained over a 12-week interval from community-dwelling elders. *Journal of Hand Therapy* 18, 4 (2005), 426–428. https://doi.org/10.1197/j.jht.2005.07.003

[8] Carlos A Celis-Morales, Paul Welsh, Donald M. Lyall, Lewis Steell, Fanny Petermann, Jana Anderson, Stamatina Iliodromiti, Anne Sillars, Nicholas Graham, Daniel F. Mackay, Jill P. Pell, Jason M. R. Gill, Naveed Sattar, and Stuart R. Gray. 2018. Associations of grip strength with cardiovascular, respiratory, and cancer outcomes and all cause mortality: Prospective cohort study of half a million UK Biobank participants. *theBmj* 361 (2018), 1651–1661. https://doi.org/10.1136/bmj.k1651

[9] Farooq Dar, Hilary Emenike, Zhigang Yin, Mohan Liyanage, Rajesh Sharma, Agustin Zuniga, Mohammad A Hoque, Marko Radeta, Petteri Nurmi, and Huber Flores. 2022. The MIDAS touch: Thermal dissipation resulting from everyday interactions as a sensing modality. *Pervasive and Mobile Computing* 84 (2022), 1–18.

[10] Michel de Mathelin, Florent Nageotte, Philippe Zanne, and Birgitta Dresp-Langley. 2019. Sensors for expert grip force profiling: towards benchmarking manual control of a robotic device for surgical tool movements. *Sensors* 19, 20 (2019), 4575. https://doi.org/10.3390/

s19204575

[11] Walaa M El-Sais and Walaa S Mohammad. 2014. Influence of different testing postures on hand grip strength. *European Scientific Journal* 10, 36 (2014), 290–301. https://eujournal.org/index.php/esj/article/view/4904

[12] Hilary Emenike, Farooq Dar, Mohan Liyanage, Rajesh Sharma, Agustin Zuniga, Mohammad A. Hoque, Marko Radeta, Petteri Nurmi, and Huber Flores. 2021. Characterizing everyday objects using human touch: Thermal dissipation as a sensing modality. In *Proceedings of the IEEE International Conference on Pervasive Computing and Communications (PerCom'21)*. IEEE, Kassel, Germany, 1–8. https://doi.org/10.1109/PERCOM50583.2021.9439120

[13] Francisco Espinoza, Pierre Le Blay, Denis Coulon, Sylvain Lieu, Janet Munro, Christian Jorgensen, and Yves-Marie Pers. 2016. Handgrip strength measured by a dynamometer connected to a smartphone: A new applied health technology solution for the self-assessment of rheumatoid arthritis disease activity. *Rheumatology* 55, 5 (2016), 897–901. https://doi.org/10.1093/rheumatology/kew006

[14] Junjun Fan, Xiangmin Fan, Feng Tian, Yang Li, Zitao Liu, Wei Sun, and Hongan Wang. 2018. What is that in your hand? Recognizing grasped objects via forearm electromyography sensing. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 4 (2018), 1–24. https://doi.org/10.1145/3287039

[15] Huber Flores, Agustin Zuniga, Naser Hossein Motlagh, Mohan Liyanage, Monica Passananti, Sasu Tarkoma, Moustafa Youssef, and Petteri Nurmi. 2020. Penguin: Aquatic plastic pollution sensing using AUVs. In *Proceedings of the ACM Workshop on Micro Aerial Vehicle Networks, Systems, and Applications (DroNet'20)*. ACM, ACM New York, NY, USA, 1–6. https://doi.org/10.1145/3396864.3399704

[16] Nizan Friedman, Vicky Chan, Andrea N Reinkensmeyer, Ariel Beroukhim, Gregory J Zambrano, Mark Bachman, and David J Reinkensmeyer. 2014. Retraining and assessing hand movement after stroke using the MusicGlove: Comparison with conventional hand therapy and isometric grip training. *Journal of NeuroEngineering and Rehabilitation* 11, 1 (2014), 1–14. https://doi.org/10.1186/1743-0003-11-76

[17] Mayank Goel, Jacob Wobbrock, and Shwetak Patel. 2012. GripSense: Using built-in sensors to detect hand posture and pressure on commodity mobile phones. In *ACM Symposium on User Interface Software and Technology*. ACM, New York, NY, USA, 545–554. https://doi.org/10.1145/2380116.2380184

[18] Weixi Gu, Yuxun Zhou, Zimu Zhou, Xi Liu, Han Zou, Pei Zhang, Costas J Spanos, and Lin Zhang. 2017. SugarMate: Non-intrusive blood glucose monitoring with smartphones. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 3 (2017), 1–27. https://doi.org/10.1145/3130919

[19] RS Guerra, I Fonseca, F Pichel, MT Restivo, and TF Amaral. 2014. Hand length as an alternative measurement of height. *European Journal of Clinical Nutrition* 68, 2 (2014), 229–233. https://doi.org/10.1038/ejcn.2013.220

[20] Jing Han, Chloë Brown, Jagmohan Chauhan, Andreas Grammenos, Apinan Hasthanasombat, Dimitris Spathis, Tong Xia, Pietro Cicuta, and Cecilia Mascolo. 2021. Exploring automatic COVID-19 diagnosis via voice and symptoms from crowdsourced data. In *Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP'21)*. IEEE, Toronto, ON, Canada, 8328–8332. https://doi.org/10.1109/ICASSP39728.2021.9414576

[21] Jing Han, Tong Xia, Dimitris Spathis, Erika Bondareva, Chloë Brown, Jagmohan Chauhan, Ting Dang, Andreas Grammenos, Apinan Hasthanasombat, Floto Floto, Andres, Cicuta Piero, and Mascolo Cecilia. 2021. Sounds of COVID-19: Exploring realistic performance of audio-based digital testing. *npj Digital Medicine* 5 (2021), 1–9. https://doi.org/10.1038/s41746-021-00553-x

[22] Katrin Hänsel, Akram Alomainy, and Hamed Haddadi. 2016. Large scale mood and stress self-assessments on a smartwatch. In *ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct (UbiComp '16)*. ACM, New York, NY, USA, 1180–1184. https://doi.org/10.1145/2968219.2968305

[23] Christian Holz and Edward J Wang. 2017. Glabella: Continuously sensing blood pressure behavior using an unobtrusive wearable device. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 3 (2017), 1–23. https://doi.org/10.1145/3132024

[24] James M Hunter, Lawrence H Schneider, Evelyn J Mackin, and Anne D Callahan. 1990. Rehabilitation of the hand: Surgery and therapy. In *Rehabilitation of the hand: Surgery and therapy*. St. Louis: Mosby, USA, 1258–1258.

[25] Sinh Huynh, Rajesh Krishna Balan, JeongGil Ko, and Youngki Lee. 2019. VitaMon: Measuring heart rate variability using smartphone front camera. In *Proceedings of the ACM Conference on Embedded Networked Sensor Systems (SenSys'19)*. ACM, New York, NY, United States, 1–14. https://doi.org/10.1145/3356250.3360036

[26] Kevin Jiokeng, Gentian Jakllari, and André-Luc Beylot. 2021. HandRate: Heart rate monitoring while simply holding a smartphone. In *Proceedings of IEEE International Conference on Pervasive Computing and Communications (PerCom'21)*. IEEE, Kassel, Germany, 1–11. https://doi.org/10.1109/PERCOM50583.2021.9439134

[27] Kee-Eung Kim, Wook Chang, Sung-Jung Cho, Junghyun Shim, Hyunjeong Lee, Joonah Park, Youngbeom Lee, and Sangryoung Kim. 2006. Hand grip pattern recognition for mobile user interfaces. In *Proceedings of the ACM Conference on Innovative Applications of Artificial Intelligence (IAAI'06)*. ACM, Boston Massachusetts, USA, 1789–1794. https://doi.org/10.5555/1597122.1597138

[28] Yoojung Kim, Hee-Tae Jung, Joonwoo Park, Yangsoo Kim, Nathan Ramasarma, Paolo Bonato, Eun Kyoung Choe, and Sunghoon Ivan Lee. 2019. Towards the design of a ring sensor-based mHealth system to achieve optimal motor function in stroke survivors. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 3, 4 (2019), 1–26. https://doi.org/10.1145/3369817

[29] Hiroshi Kinoshita, Satoru Kawai, and Komei Ikuta. 1995. Contributions and co-ordination of individual fingers in multiple finger prehension. *Ergonomics* 38, 6 (1995), 1212–1230. https://doi.org/10.1080/00140139508925183

[30] Setor K Kunutsor, Ari Voutilainen, and Jari A Laukkanen. 2020. Handgrip strength improves prediction of type 2 diabetes: A prospective cohort study. *Annals of Medicine* 52, 8 (2020), 471–478. https://doi.org/10.1080/07853890.2020.1815078

[31] Elina Kuosmanen, Valerii Kan, Aku Visuri, Simo Hosio, and Denzil Ferreira. 2020. Let's Draw: Detecting and measuring parkinson's disease on smartphones. In *Proceedings of the Conference on Human Factors in Computing Systems (CHI'20)*. ACM, Honolulu, HI, USA, 1–9. https://doi.org/10.1145/3313831.3376864

[32] Yongbo Liang, Mohamed Elgendi, Zhencheng Chen, and Rabab Ward. 2018. An optimal filter for short photoplethysmogram signals. *Scientific Data* 5, 1 (2018), 1–12. https://doi.org/10.1038/sdata.2018.76

[33] Rongrong Liu, Florent Nageotte, Philippe Zanne, Michel de Mathelin, and Birgitta Dresp-Langley. 2021. Wearable sensor technology for individual grip force profiling. *Automation, Robotics & Communications for Industry 4.0* 1 (2021), 12–13.

[34] Niko Mäkitalo, Daniel Flores-Martin, Huber Flores, Eemil Lagerspetz, Francois Christophe, Petri Ihantola, Masiar Babazadeh, Pan Hui, Juan Manuel Murillo, Sasu Tarkoma, and Tommi Mikkonen. 2020. Human data model: Improving programmability of health and well-being data for enhanced perception and interaction. *ACM Transactions on Computing for Healthcare* 1, 4 (2020), 1–39. https://doi.org/10.1145/3402524

[35] Nicola M Massy-Westropp, Tiffany K Gill, Anne W Taylor, Richard W Bohannon, and Catherine L Hill. 2011. Hand grip strength: Age and gender stratified normative data in a population-based study. *BMC Research Notes* 4, 1 (2011), 1–5. https://doi.org/10.1186/1756-0500-4-127

[36] Ryan McGrath, Nathaniel Johnson, Lukus Klawitter, Sean Mahoney, Kara Trautman, Caroline Carlson, Ella Rockstad, and Kyle J Hackney. 2020. What are the association patterns between handgrip strength and adverse health conditions? A topical review. *SAGE Open Medicine* 8 (2020), 1–12. https://doi.org/10.1177/2050312120910358

[37] Ryan McGrath, Sheria G Robinson-Lane, Summer Cook, Brian C Clark, Stephen Herrmann, Melissa Lunsman O'Connor, and Kyle J Hackney. 2019. Handgrip strength is associated with poorer cognitive functioning in aging Americans. *Journal of Alzheimer's Disease* 70, 4 (2019), 1187–1196. https://doi.org/10.3233/JAD-190042

[38] Rita Pavasini, Matteo Serenelli, Carlos A Celis-Morales, Stuart R Gray, Kazuhiro P Izawa, Satoshi Watanabe, Eloisa Colin-Ramirez, Lilia Castillo-Martínez, Yasuhiro Izumiya, Shinsuke Hanatani, Yoshiro Onoue, Kenichi Tsujita, Peter S Macdonald, Sunita R Jha, Véronique L Roger, Sheila M Manemann, Juan Sanchis, Vicente Ruiz, Giulia Bugani, Elisabetta Tonet, Roberto Ferrari, Stefano Volpato, and Gianluca Campo. 2019. Grip strength predicts cardiac adverse events in patients with cardiac disorders: An individual patient pooled meta-analysis. *Heart* 105, 11 (2019), 834–841. https://doi.org/10.1136/heartjnl-2018-313816

[39] Philip Quinn, Seungyon Claire Lee, Melissa Barnhart, and Shumin Zhai. 2019. Active edge: Designing squeeze gestures for the google pixel 2. In *Proceedings of the Conference on Human Factors in Computing Systems (CHI'19)*. ACM, Glasgow, Scotland UK, 1–13. https://doi.org/10.1145/3290605.3300504

[40] Robinson Ramírez-Vélez, Jorge Enrique Correa-Bautista, Antonio García-Hermoso, Carlos Alberto Cano, and Mikel Izquierdo. 2019. Reference values for handgrip strength and their association with intrinsic capacity domains among older adults. *Journal of Cachexia, Sarcopenia and Muscle* 10, 2 (2019), 278–286. https://doi.org/10.1002/jcsm.12373

[41] Philippe Renevey, Ricard Delgado-Gonzalo, Alia Lemkaddem, Martin Proença, Mathieu Lemay, Josep Solà, Adrian Tarniceriu, and Mattia Bertschi. 2017. Optical wrist-worn device for sleep monitoring. In *EMBEC & NBC 2017*. Springer, Tampere, Finland, 615–618. https://doi.org/10.1007/978-981-10-5122-7_154

[42] Helen C Roberts, Hayley J Denison, Helen J Martin, Harnish P Patel, Holly Syddall, Cyrus Cooper, and Avan Aihie Sayer. 2011. A review of the measurement of grip strength in clinical and epidemiological studies: Towards a standardised approach. *Age and Ageing* 40, 4 (2011), 423–429. https://doi.org/10.1093/ageing/afr051

[43] Lisa Schrader, Agustín Vargas Toro, Sebastian Konietzny, Stefan Rüping, Barbara Schäpers, Martina Steinböck, Carmen Krewer, Friedemann Müller, Jörg Güttler, and Thomas Bock. 2020. Advanced sensing and human activity recognition in early intervention and rehabilitation of elderly people. *Journal of Population Ageing* 13 (2020), 139–165. https://doi.org/10.1007/s12062-020-09260-z

[44] Adwait Sharma, Michael A Hedderich, Divyanshu Bhardwaj, Bruno Fruchard, Jess McIntosh, Aditya Shekhar Nittala, Dietrich Klakow, Daniel Ashbrook, and Jürgen Steimle. 2021. SoloFinger: Robust microgestures while grasping everyday objects. In *Proceedings of Conference on Human Factors in Computing Systems (CHI'21)*. ACM, Yokohama, Japan, 1–15. https://doi.org/10.1145/3411764.3445197

[45] Sari Stenholm, Janne Sallinen, Annemarie Koster, Taina Rantanen, Päivi Sainio, Markku Heliövaara, and Seppo Koskinen. 2011. Association between obesity history and hand grip strength in older adults—exploring the roles of inflammation and insulin resistance as mediating factors. *Journals of Gerontology Series A: Biomedical Sciences and Medical Sciences* 66, 3 (2011), 341–348. https://doi.org/10.1093/gerona/glq226

[46] Jason Tallis, Rob S James, and Frank Seebacher. 2018. The effects of obesity on skeletal muscle contractile function. *Journal of Experimental Biology* 221, 13 (2018), 1–14. https://doi.org/10.1242/jeb.163840

[47] D Trosclair, D Bellar, LW Judge, J Smith, N Mazerat, and A Brignac. 2011. Hand-grip strength as a predictor of muscular strength and endurance. *The Journal of Strength & Conditioning Research* 25 (2011), S99. https://doi.org/10.1097/01.JSC.0000395736.42557.bc

[48] Peter M Visscher. 2008. Sizing up human height variation. *Nature genetics* 40, 5 (2008), 489–490. https://doi.org/10.1038/ng0508-489

[49] Shibo Zhang, Yuqi Zhao, Dzung Tri Nguyen, Runsheng Xu, Sougata Sen, Josiah Hester, and Nabil Alshurafa. 2020. NeckSense: A multi-sensor necklace for detecting eating activities in free-living conditions. *Proceedings of the ACM on Interactive, Mobile, Wearable*

*and Ubiquitous Technologies* 4, 2 (2020), 1–26. https://doi.org/10.1145/3397313
[50] Paula Zuccotti. 2015. *Every thing we touch: A 24-hour inventory of our lives.* Penguin UK, UK.
[51] Agustin Zuniga, Huber Flores, and Petteri Nurmi. 2021. Ripe or rotten? Low-cost produce quality estimation using reflective green light sensing. *IEEE Pervasive Computing* 20, 3 (2021), 60–67. https://doi.org/10.1109/MPRV.2021.3074474