Balancing Accuracy and Fun: Designing Camera Based Mobile Games for Implicit Heart Rate Monitoring

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ABSTRACT

Heart rate monitoring is widely used in clinical care, fitness training, and stress management. However, tracking individuals' heart rates faces two major challenges, namely *equipment availability* and *user motivation*. In this paper, we present a novel technique, LivePulse Games (LPG), to measure users' heart rates in real time by having them play games on unmodified mobile phones. With LPG, the heart rate is calculated by detecting changes in transparency of users' fingertips via the built-in camera of a mobile device. More importantly, LPG integrate users' camera lens covering actions as an essential control mechanism in game play, and detect heart rates implicitly from *intermittent* lens covering actions. We explore the design space and trade-offs of LPG through three rounds of iterative design. In a 12-subject user study, we found that LPG are fun to play and can measure heart rates accurately. We also report the insights for balancing measurement speed, accuracy, and entertainment value in LPG.

Author Keywords

Heart rate, mobile phone, multi-modal interface, game design, serious game, ECG, quantified self.

ACM Classification Keywords

H5.2. Information interfaces and presentation (e.g., HCI): User Interfaces.

General Terms

Design, Experimentation, Human Factors.

INTRODUCTION

Heart rate is one important vital sign in health care [6, 29]. For healthy people, resting heart rate (RHR) is also an essential physiological marker of physical fitness [7, 30, 38], and expected life span [13]. Heart rate has been used in fitness training [19, 20] and competitive sports for managing work-out intensity and balancing physical exertion. Both continual readings of heart rates [5, 15, 37, 33] and heart rate variability, a.k.a. HRV [27, 29, 32, 33], can predict a user's physiological state, including cognitive workload and mental stress levels, in contexts such as computer user interfaces [29, 33], traffic control [29], longitudinal monitoring of emotion and food intake [5], and intelligent tutoring [15]. Therefore, the efficient measurement of heart rate can be of great significance across scenarios involving physical health, mental activities or a combination of both.

Unfortunately, most heart rate measurement methods are either time-consuming[1], or require special measurement equipment [25] that may not be available to a wide audience. For example, manual pulse counting with fingers may be tedious, and inaccurate. More precise methods include the Electrocardiograph (ECG) [22, 25] and pulse oximeters [25, 35]. These dedicated heart rate monitoring devices share at least three disadvantages. First, the costs of these devices could prevent wide adoption in everyday life. Second, it is not convenient to carry and use the devices "on the go". Last but not least, existing methods provide little immediate benefits or *intrinsic motivation* to users and thus may be tedious to track heart rate in a longitudinal setting.

Figure 1. Real-time heart rate measurement via LivePulse Games (left: City Defender, right: Gold Miner).

To overcome the limitations of existing techniques, we have developed LivePulse Games (LPG, figure 1) to measure users' heart rates in real time by having them play serious games on unmodified mobile phones. LPG calculate heart rates by detecting the transparency change of fingertips via the built-in camera (i.e. commodity camera

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[1] In both the preparation phase and the actual measurement stage.

based photoplethysmography (PPG) [2, 4, 12, 26]). More importantly, LPG integrate users' camera lens covering actions as essential parts of the game so as to detect heart rate *implicitly* during game play. LPG combine unique designs in both algorithms and game play to achieve accurate and robust heart rate extraction through intermittent finger lens covering actions. With the increasing popularization of smartphones, LPG have the potential to measure heart rate longitudinally in a natural and enjoyable way.

Different from biofeedback games [21, 23, 31] that *use* heart rates to *augment* game play, LPG is a game based approach for heart rate *measurement*. To avoid confounders, we intentionally choose not to use heart rates collected from LPG to change game states at this stage.

This paper offers four important contributions:

- Expanding the design space of camera based heart rate monitoring from continual, explicit signals to *intermittent* and *implicit* signals;
- A robust and accurate algorithm with fast bootstrap time that can detect heart rate from noisy and intermittent signals in real time on mobile devices;
- A set of insights and trade-offs learned from designing engaging LivePulse Games that integrate lens covering actions as an essential control mechanism;
- A 12-subject user study that validates the reported approaches and clarifies the feasibility, usability, and design insights involved.

In the following sections, we first explain in detail the algorithm for detecting human heart rate through intermittent camera lens covering actions; next, we discuss the trade-offs in game design when balancing detection accuracy, detection speed, and game intensity; after that, we share the insights and lessons learned from three rounds of iterative design. Finally, we report the results of a 12-subject user study, including the accuracy of LPG and the impact of game intensity on the speed and accuracy of heart rate measurement.

RELATED WORK

Heart Rate Detection Techniques

The most widely adopted approaches for detecting heart rate are based on Electrocardiography (ECG or EKG, usually in the form factor of chest band, wrist band, or watch) and pulse oximetry (i.e. blood oxygen saturation or blood oxygenation). Researchers have created highly portable, low power, wireless mobile ECG [22] and blood oxygen saturation measurement devices [35] in the past. A state-of-the-art device, the Berkeley Tricorder [22] by Naima and Canny, is capable of measuring a subject's ECG, EMG, respiration, and motion via a 2 by 2 inch Bluetooth device. Despite the steady drop on manufacturing costs [25] for such devices, they are still not readily available for most users in an everyday setting. For example, Depending on the brand, form factor, and communication interface supported, a heart rate monitoring watch (e.g. Omron HR-100CN, MIO Alpha, Basis, or Apple Watch) costs from US$30 to US$350 as of September 2014. Low cost devices like Omron HR-100CN usually do not have digital interfaces for sending data to computers.

LivePulse Games rely on photoplethysmography (PPG) [36] to detect heart rates. Although the fundamental mechanism of PPG through commodity built-in cameras on mobile phones has been explored by both commercial applications (e.g. Instant Heart Rate [12], Cardiograph [4]) and researchers [2, 26] in the past, all existing methods require users to cover and hold the mobile phone camera lens intentionally and steadily for an extended amount of time before receiving heart rate estimates. While these systems eliminated the equipment availability challenge, none of them attempted to address the human *motivation* challenge involved. In comparison, LPG explore the feasibility of extracting heart rates from *implicit*, *intermittent* lens covering actions during mobile game plays, and design engaging mobile games that balance measurement speed, accuracy and entertainment value.

It's also possible to calculate heart rate by recording and analyzing thermal changes [10], color changes [27, 28], and involuntary motion [1] of human faces in video. However, such approaches are more sensitive to environmental illumination changes and the component analysis (PCA [1] or ICA [27, 28]) techniques used also require users to stay still for an extended amount of time (e.g. 60+ second). Still, facial video analysis from a mobile device's front camera could be an interesting future direction to explore with LivePulse Games.

Heart Rate in Interactions

Heart rate has been used by researchers in fitness training, balancing exertion [19, 20] in social sports, measuring mental workload [29] and stress [32], and developing adaptive intelligent tutoring systems (ITS) [15].

TripleBeat by Oliveira et al. [24] is a mobile fitness training application that uses heart rate measured from an ECG instrumented chestband to encourage runners to better achieve a predefined exercise goal. Nenonen et al. [23] allowed users to control parameters of video games (e.g. speed, slope of the road) by adjusting their heart rate. Mueller et al [19, 20] and Stach et al [31] leveraged the heart rate as an input to balance participants' performance in jogging to motivate people with lower fitness level to "exercise together". Instead of *using* heart rates as a supplemental *input* channel to control the in-game parameters adaptively, LivePulse Games *motivate* users to play games and heart rates are generated as an *implicit output* of game plays.

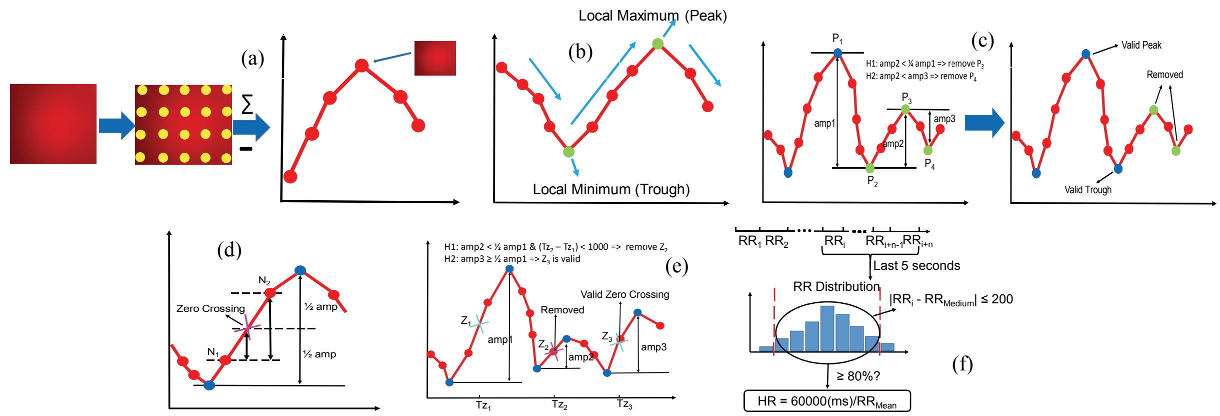

Figure 2. Major steps of the LivePulse algorithm (a. signal preprocessing; b. locating raw local peaks & valleys; c. locating valid peaks & valleys; d. locating raw zero-crossings; e. locating valid zero-crossings; f. calculating heart rate).

A user's changing heart rhythms affect not only the heart itself but also the brain's ability to process information and manage emotion. Researchers have discovered that both the heart rate [37] and heart rate variability (HRV) [32] have strong correlations with stress and persistently elevated heart rate is a sign of chronic stress [37]. It's worth noticing that both heart rate and HRV can and are regularly used for short term stress measurements. In [33], heart rate was a more accurate marker of external stress than HRV. Heart rate will be confounded by physical activity but the user will be aware of whether or not they have been active, and elevated HR otherwise is a sign of stress. Rowe [29] investigated the use of heart rate signals to assess the impact of a monitoring interface on user mental effort. Poh et al [27] demonstrated the feasibility of extracting Heart rate variability (HRV) from 1 minute of continual color facial images[2]. We believe adaptive systems that infer cognitive workload [29], attention [15], or emotion [5] from heart rates could benefit from LivePulse Games' pervasive, non-invasive real-time heart rate monitoring.

Serious Games

Many researchers have explored the use of games as a motivation mechanism for performing desirable but challenging/tedious activities such as education [34], fitness training, behavior change [5], and device calibration [8]. LivePulse Games are serious games designed from the ground up to balance the speed and accuracy of heart rate tracking with fun in game play.

DESIGNING LIVEPULSE GAMES

There are two main challenges in designing LivePulse Games. The first task is to formulate an algorithm that can detect human heart rate *reliably* and *efficiently* on unmodified mobile phones, even during noisy and *sporadic* activities. This task eliminates the need for specialized heart rate monitoring equipment, making it feasible to measure heart rate in different contexts. The second task consists of designing interactions that integrate the slightly "bizarre" requirement in PPG (i.e. covering the camera lens with fingertip and holding it steadily) *naturally* into mobile game play. The second task addresses the motivational challenges in heart rate monitoring, converting heart rate measurement from a dull routine into a fun and engaging activity.

Camera Based Heart Rate Detection

LivePulse Games rely on the back camera of mobile phones to detect heart rates. The underlining theory is: in every cardiac circle, the heart pumps blood to the capillary vessels of a human body, including fingertips. The arrival of fresh blood changes the transparency of fingertips. Such transparency changes correlate directly with heart rates, and can be detected by the built-in camera when the user covers the lens of the camera with her finger tip.

Although camera based heart rate detection algorithms have been reported before [2, 26], the previous algorithms were not optimized for extracting heart rates from *noisy* and *intermittent* covering actions and both algorithms require a long bootstrap time before generating the first estimate (20 seconds in [2], 9 seconds in [26]) in clean and continual measurements. For commercial products such as Instant Heart Rate [12], and Cardiograph [4], their algorithms were never disclosed and neither app could extract heart rates if there are finger movements during the measurement[3]. To achieve better robustness and shorter bootstrap time for noisy, *intermittent* signals from *implicit* user interactions, we designed our own algorithm that meets the speed, accuracy and robustness requirements of LPG.

Instead of using component analysis and then transforming signals to the frequency domain [1, 27, 28], the LivePulse algorithm extracts heart rate information directly from the relatively noisy temporal signal. We made this decision for

[2] In standardized *clinical* diagnosis [18], 24-hour is required for measuring *long-term* HRV. Malik et al [18] also suggested 5 min for reliable *short-term* HRV and 1-2 min as the minimal time HRV in *clinical* use.

[3] According to the authors' experiments in July 2014, the minimal bootstrap time for the 4.0 version of Instant Heart Rate [12] is 7 seconds and 15 seconds of uninterrupted holding is required for a reliable estimate. The app resets its progress when there is significant finger movement during the measurement.

two reasons: 1) Given the intermittent nature of the envisioned usage scenario, we do not assume that consistent, uninterrupted signals will arrive for an extended amount of time, which is usually necessary for transformations such as PCA/ICA; 2) We expect the LivePulse algorithm could run efficiently on mobile devices in real-time and leave enough CPU power to handle the graphics and multimedia effects during game plays.

In the LivePulse algorithm, the camera is set in preview mode, capturing 176x144 pixel color images at a rate of 30 frames per second (a minimal frame rate of 15 fps is required). We disable the automatic focus function and the automatic white balance function to avoid interference with our algorithm. Optionally, we can turn the built-in flashlight on to improve performance in low illumination conditions.

When a lens covering action is detected (LPG uses the *Static LensGesture* detection algorithm in [40]), the LivePulse algorithm extracts heart rates via a 6-step, heuristic based process detailed below.

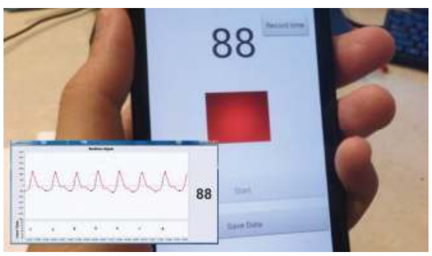

Figure 3. A prototype of LivePulse running on a mobile phone with real-time heart-rate signals shown in a PC application.

Step 1: The LivePulse algorithm first converts each frame into one time-stamped heart beat sample point via equal distance sampling and the summation of 800 points on the Y channel in each frame (Figure 2.a). The signal is flipped in y-axis to match waveform output tradition of existing PPG techniques [36]. *Step 2*: The algorithm then detects all the local peaks and valleys in the converted temporal sequence signal by measuring the local curvature changes (Figure 2.b). *Step 3*: Adjustable threshold based heuristics are applied to eliminate small and noisy local minima/maxima points (Figure 2.c). *Step 4 and 5*: Instead of estimating heart rates from two adjacent peaks/valleys directly, we found that it is more reliable to estimate and interpolate the time stamps of zero-crossing points [4] between peaks and valleys and then derive heart rates from the time differences between two adjacent time stamps of zero-crossing points (Figure 2.d 2.e). *Step 6*: To further improve the robustness of LivePulse, we save and sort the time stamp distances between adjacent zero-crossing points during the past five seconds. Real time heart rate is reported when at least 80% of the time-stamp distances are within a given variation range (25%) (Figure 2.f). Since the heuristic in step 6 doesn't rely on hard coded parameters for noise filtering, it worked robustly in LivePulse Games involving frequent motion gestures.

LivePulse can extract heart rates from people with different skin melanin levels (e.g. white, yellow, black) when the flash is on according to our informal tests.

Figure 3 shows a tool we created for debugging the LivePulse algorithm. Finger transparency information are collected on mobile phones and streamed to a PC for visualization and analysis. After debugging, the actual LivePulse Games run solely on mobile devices in real time.

Intermittent Lens Covering Actions

The above method requires users to cover the camera lens with their fingers for an extended duration. When there are breaks in the heart beat input (caused by releasing the finger from the camera lens), our algorithm suspends updating zero-crossing intervals until a finger covering action is detected. The LivePulse algorithm then applies heuristic steps 1 - 4 on temporal samples after the new covering action, concatenates the first newly detected zero-crossing point, and updates the time stamps for all the follow-up zero-crossing points by subtracting the time gap lapsed between adjacent camera lens covering actions. When compared with existing frequency domain techniques [27, 28], our technique has a short bootstrap latency (mostly 2-3 seconds), and is capable of extracting heart rates from intermittent covering scenarios that existing systems [4, 12] couldn't handle.

From LivePulse to LivePulse Games

In order to make the heart rate monitoring task more engaging, we have designed games that leverage the LivePulse algorithm and integrate heart beat measurement *implicitly* in the game play.

Two major concerns arise when designing LivePulse Games. First, what is the best trade-off in balancing the fun/engaging factor and the measurement accuracy during a game play? Second, what are the effective techniques to integrate lens covering actions required by LivePulse *naturally* into the games?

We clarify the first concern with a thought experiment. According to the working mechanism of LivePulse, the algorithm works best when a user covers the camera lens completely and steadily all the time. Following this trait, in one extreme situation, we could use the camera lens as a "*power switch*", i.e. the game continues when a user covers the camera lens, and pauses when the finger leaves the lens. Although heart rates can be measured with minimal interruptions, such scenario will lead to bad game playing experiences for two reasons: 1) the lens covering action is actually isolated from the actual in-game interactions; and 2) the finger covering action needed becomes an *extra*

[4] The zero crossing line is dynamic, defined as the line with the mean Y values between two adjacent valley and peak (figure 2.d). The time stamps of zero crossing points (i.e. z1, z2, z3 in figure 2.e) are linear interpolated values between two adjacent time stamps.

burden rather than an entertaining factor. As a result, users could feel bored and start to look for equivalent games that do not require lens covering.

In the other extreme situation, if the lens covering action is used as a high frequency input channel, e.g. directly controlling missile firing in a "shoot-em-up" video game, the game play could be engaging and satisfying, but the underlying algorithm may have trouble in getting reliable readings from extremely brief and unstable finger touches.

As illustrated by the two extreme situations, there exists a performance/reliability vs. fun trade-off highlighted in designing LPG. We keep this trade-off in mind and we also run controlled experiments to quantify the trade-offs by manipulating the intensity of games in our user study.

In addition to the brute-force "*power switch*" metaphor, the lens covering gesture can serve as a "*trigger*" to activate an in-game event. In this scenario the camera lens is no different[5] from a push button mounted on the back of the mobile phone. In this mode, the timing and frequency of covering are used in game control. The lens covering gesture can also be used as a "*clutch*" or a gas pedal. In this paradigm, covering the lens steadily will switch certain in-game object into a different mode (e.g. charging, accelerating etc). In the "*clutch*" mode, players use the timing and duration of covering as the primary control mechanism. With these observations in mind, we explore the design space of using lens covering actions by integrating diversified lens control mechanisms in different LivePulse Games.

Figure 4. Screenshots of the three games: City Defender (left), Gold Miner (middle), and Bug Defender (right).

There are two supplementary benefits for integrating the unique affordance of users' lens covering gestures in game play. First, this approach could free a user's index finger in the hand holding the phone for game play. This index finger stays idle during most interactions. Second, the edge and bezel of cameras are usually made of different materials and on different surface levels, which could provide natural tactile feedback for direct touch operations on the lens.

When designing LPG, we also explore different combinations of input modalities (touch screen, accelerometer), and interaction types (one-hand, two-hand) in game design. These intentional design space variations allow us to explore the impact of lens covering frequency to heart rate measurement accuracy, as well as the impact of device motion in game play (e.g. wrist rotation, screen tapping) to heart rate measurements.

Through three rounds of iterative design, we created three LivePulse Games: City Defender, Gold Miner, and Bug Defender (figure 4) to test pervasive, non-invasive heart rate monitoring on mobile phones.

City Defender

The City Defender game (figure 4, left) allows users to protect a city by controlling a powerful, but slow anti-aircraft artillery. Users tap on the screen to fire bullets from artillery, move the artillery and collect rescue packages. Each user action costs a certain amount of energy and users lose the ability to fire or move when the energy bar is empty. Users can cover and hold the lens to recharge the energy bar gradually. However, the antiaircraft artillery cannot be moved or fired when the energy bar is charging. Destroying all the enemy fighters clears a stage and being hit by five bombs loses the game.

In order to get high scores in City Defender, users need to make strategic plans on the timing and frequency of four mutually exclusive activities (i.e. firing, charging, collecting rescue packages, and dodging enemy attacks) and execute them properly. For example, collecting a rescue package may not be the right choice if such action moves the artillery to a disadvantaged position.

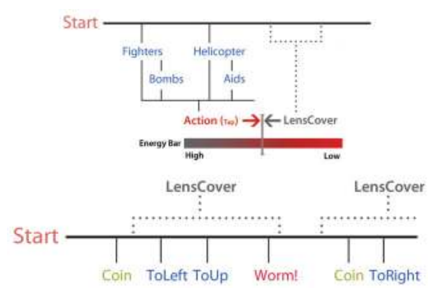

Figure 5. Play workflows for CityDefender (top) and Gold Miner (bottom).

City Defender requires users to perform coordinated actions with both hands. The charging action is completed by the user's index finger on the hand holding the phone, and the firing/moving actions are completed on the touch screen by the other hand. Figure 5 (top) shows the play workflow of City Defender.

Gold Miner

Gold Miner (Figure 4, middle) is similar to the classic snake game on Nokia phones with unique tweaks. In this game, users control an explorer to collect randomly placed coins in the scene. Users tilt the phone in different directions (i.e. left, right, up, and down) to move the explorer. The explorer cannot hit bushes (staying still) or enemy worms (chasing the explorer when the exploring is

[5] Despite the 33 ms latency caused by the camera frame rate and the 2.7 ms latency for detecting a lens covering action [40].

moving) during movements. Worms start chasing the explorer only when the explorer is moving. The camera lens is used as a clutch to initiate motion gestures for controlling the explorer in Gold Miner. Releasing the finger from the camera lens will stop both the explorer and the chasing worm.

To become a successful player of Gold Miner, users need to 1) decide wisely on when to move and when to stop (associated with using the lens covering action as a clutch); 2) planning long and feasible moving trajectories and move in-game explorer timely via phone tilting. Figure 5 (bottom) shows the play workflow of Gold Miner.

Bug Defender

Bug Defender (Figure 4, right) is a farming game where users aim to kill worms in their farms. Users cover the camera lens to charge a water gun and tap on the screen fire the water gun and shot at the location tapped. Worms can only be killed when the worm color matches the corresponding screen orientation, i.e. when red worms appear, users need to put the mobile phone in landscape mode and shoot; when blue worms appear, users need to put the mobile phone to portrait mode.

Implementation

LivePulse Games were written in Java running on the Android 4.0 operating system. We used the AndEngine (http://www.andengine.org/) for OpenGL ES encapsulation and game scene management. Excluding third party libraries, the three LivePulse Games have a total of 10,398 lines of code in Java. Our games have been tested on Google Nexus S, Galaxy Nexus, and Nexus 4 smart phones.

Iterative Design Process

LivePulse Games went through three rounds of iterative design. Major design changes were made based on users' comments and feedback in two pilot studies (six subjects and four subjects respectively). LPG were able to extract heart rate information from all the game play sessions, the mean error rate (MER) in the pilot study sessions were satisfactory (< 7%).

In addition to bug fixes, and adding additional in-game feedback (e.g. the low energy alarm, lens covering state), major usability issues identified and addressed through pilot studies include:

Engaging both causal users and "hard-core" players. Pilot study users have highly diversified experiences in mobile game play. While it could take a non-gamer a couple of minutes and a few rounds of trial-and-error to learn to survive in LPG, some "hard-core" players had already felt "not challenging enough" within the same amount of time. To address this issue, we revised LPG to provide multiple levels of intensity under the same play workflow by varying the frequency, number, appearance pattern of enemies (e.g. enemy fighters, coins, and bugs) on screen. We also added the Producer-Consumer pattern [3] to the play flow of each game to increase the diversity of game play and give "hard-core" players opportunities to devise and execute wise strategic plans to unlock higher score and achievements in the game.

Avoiding modality overloading. For example, the initial design of Bug Defender requires input from three different modalities, i.e. screen tapping, lens covering, and screen orientation change. While participants found the idea of multiple input modalities exciting, pilot study results showed that it was also challenging to coordinate three modalities accurately in parallel at the learning stage, even for "hard-core" players. As a result, when adopting multiple input modalities as an engaging factor, we enforce the rule of "no more than two parallel modalities" in initial levels for all the updated LPG.

USER STUDY

Although we have confirmed the feasibility of LivePulse Games in the two pilot studies, a formal user study was necessary to understand the capabilities and limitations of LPG as a new mechanism for implicit heart rate measurement. We had three goals for the study. One was to quantify the accuracy of LPG and observe the impact of LPG play on heart rate (i.e. will playing LPG confound a user's resting heart rate?); The second goal was to quantitatively investigate the trade-offs between game playing intensity, entertainment and the accuracy of heart rate monitoring. Lastly, we were interested in collecting subjective feedback and observing how users play LPG.

Experimental Design

The study consisted of four parts:

Overview. We first gave participants a brief introduction to LivePulse Games and then collected background information of participants. We demonstrated City Defender and Gold Miner to the participants and explained the working mechanisms behind these games.

Measuring Heart Rate Accuracy. We measured participants' heart rates in both resting condition and two gaming settings. In the resting condition, we used a standalone LivePulse application running on a mobile phone (Figure 3) and a pulse oximeter. We let participants sit comfortably in a chair, holding the mobile phone with their left hands, and using the index finger of the left hand to cover the camera lens. We instructed participants to apply comfortable pressure when covering the lens. We attached the pulse oximeter on the index fingers of the participants' right hands. The measurement setting of Gold Miner was the same as the resting condition, because Gold Miner supports one handed game play. Since City Defender requires both hands, we attached the pulse oximeter to the ring finger of the right hand.

Playing Games at Different Intensity Levels. Participants played the City Defender game and the Gold Miner game with three different intensity levels (i.e. 2 games*3 intensity levels = 6 conditions). Different intensities were achieved by manipulating the quantity and appearance frequency of in-game enemies. Participants spent roughly two minutes in

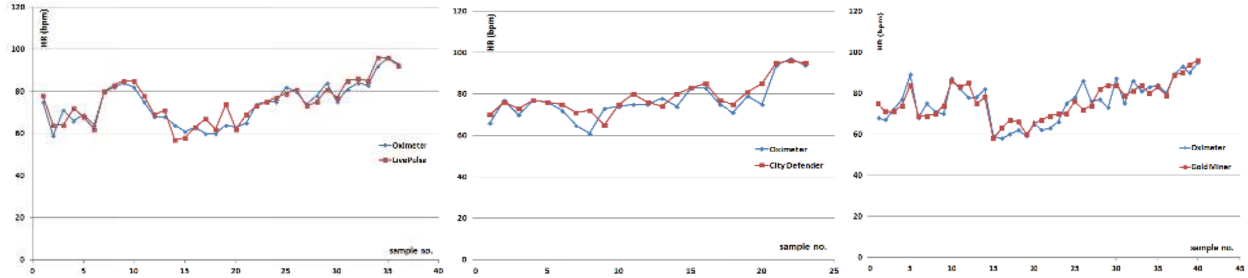

Figure 7. Heart rates (bpm) of 12 subjects (left:resting mode, middle: playing City Defender, right: playing Gold Miner) from LivePulse, LivePulse Games (red) and Oximeter (blue).

each condition. Participants took breaks between different conditions, but they were not allowed to pause or exit from the game in each condition. *The order of conditions was counterbalanced*.

Qualitative Feedback. Closing questionnaires were collected after participants completed all tasks. We also asked participants to comment on each game's difficulty levels, and describe their general feeling towards the LivePulse Games.

Participants and Apparatus

12 participants (3 female) between 19 and 27 years of age participated in our study. All the participants were undergraduate or graduate students in a local university.

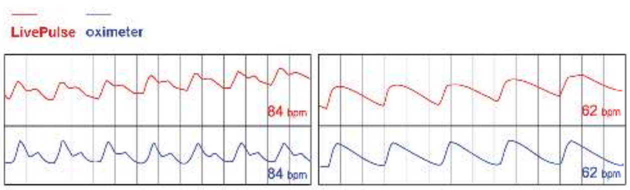

Figure 6. 14 seconds of sample heart beat signals from LivePulse (red) and oximeter (blue).

Our experiments were completed on a Google Galaxy Nexus Smartphone with a 4.65 inch, 720 x 1280 pixels display, 1.2 GHZ dual core ARM Cortex-a9 processor, running Android 4.1. It has a 5 mega-pixel back camera and a LED flash. We also used a CMS 50D pulse oximeter with a USB interface to measure heart rate. This pulse oximeter is an FDA approved, medical grade device. The accuracy of CMS 50D for pulse ratio is +/-2BPM.

EVALUATION RESULTS

LPG were able to extract all the 12 participants' heart rates successfully from all the sessions.

Accuracy

Overall, raw heart beat signals from LivePulse and the oximeter were highly consistent in both beat-to-beat interval and the actual wave shape (Figure 6).

To compare the accuracy of LivePulse quantitatively, we aligned and re-sampled readings from both LivePulse and the oximeter to 20 HZ. When treating the readings from the oximeter as the gold standard, the Mean Error Rate (MER) of LivePulse was 3.9% (-7 ~ +5 bpm, Figure 7, left) in the resting condition, 4.6% (-8 ~ +11 bpm, Figure 7, middle) when playing City Defender, and 5.0% (-14 ~ + 11, Figure 7, right) when playing Gold Miner. Analysis of variance results showed that the differences in heart rate readings from LivePulse and the oximeter were not statistically significant in all the three conditions: LivePulse in resting condition vs. Oximeter($F_{1,\ 11} = 1.64$, $p = 0.13$, n.s.), Oximeter vs. City Defender ($F_{1, 11} = 0.83$, $p = 0.40$, n.s.), Oximeter vs. Gold Miner ($F_{1, 11} = 0.23$, $p = 0.82$, n.s.). We also computed a Pearson product-moment correlation coefficient and there was a significant positive correlation between readings from LivePulse and oximeter, $r = 0.98$, $t = 15.5$, $p < 10^{-7}$.

Considering that the CMS 50D oximeter has an accuracy of +/- 2%, the accuracies of LPG in both resting condition and actual game settings are satisfactory.

Despite the relatively low MER, the maximal absolute difference could be up to 7 bpm in the resting condition, 11 bpm when playing Gold Miner and 14 bpm in Gold Miner. We attribute these outliers to noise caused by finger position/posture changes and background illumination changes. We suspect the higher maximal error rate in Gold Miner was caused by the extensive wrist movements in game plays. These outliers can be further eliminated by applying a low pass filtering algorithm or heuristics [1, 28] in situations where accuracy is more important than responsiveness.

Paradoxically, we didn't observe a major difference in heart rates between the idle mode and two active game play sessions. Among all three conditions tested, subjects' heart rates varied similarly from 56 bpm to 97 bpm. We believe this observation was caused by the "*casual*" style of current LPG and the relatively brief game play sessions. It is possible that the users' heart rates may change significantly when playing more intensive games for an extended amount of time. One piece of interesting future work would be to predict the resting heart rate from heart rate measured in intensive game play sessions via machine learning should these kinds of differences occur.

City Defender

Figure 8 shows a typical 2-minute game playing session when playing City Defender. The top row shows the raw finger transparency readings after scaling (without applying any noise filtering or interpolation algorithms). The second row shows corresponding heart rate estimates. The follow-up rows show the covering states of the lens, major user input, and the major events in the game respectively. As illustrated in Figure 8, finger transparency readings showed up immediately after each lens covering action. The first valid heart rate estimation appeared roughly 20 seconds after the game began. Interestingly, the first one or two raw finger transparency readings (i.e. within 30-60ms) after a lens covering action were usually noisy. The LPG MER can be further reduced by 1% by simply removing the first transparency reading associated with each lens covering action.

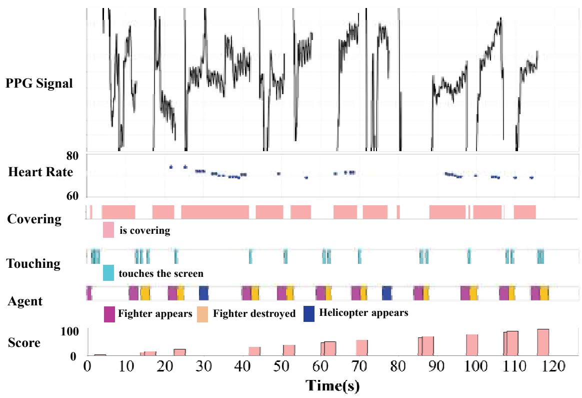

Figure 8. A 2-minute session in City Defender.

In City Defender, with the increase of the in-game intensity, the ratios of valid lens covering sessions[6] and valid lens covering durations[7] decreased consistently (figure 9). The increase of in-game difficulty level led to more frequent switches between lens covering/uncovering actions, as a result, the quality of finger transparency signal drops. In general, around 28% - 37% of lens covering time, or 33% - 43% of the lens covering sessions could generate valid heart rate estimations.

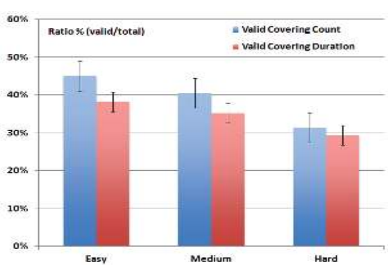

Figure 9. Heart rate estimation quality by difficulty levels in City Defender.

Figure 10 shows the histogram of the covering time needed to generate valid heart rate estimates. In most sessions, LPG generated effective heart rate estimates 2 to 4 seconds after covering the lens. Lens covering actions shorter than 2 seconds were less likely to generate valid heart rate estimates. As a result, when designing a new LivePulse Game, it is imperative to design the game dynamics in a way that a major portion of the in-game lens covering actions are longer than 2 seconds. This empirical parameter also provides an upper bound of game intensity for the current LPG algorithm.

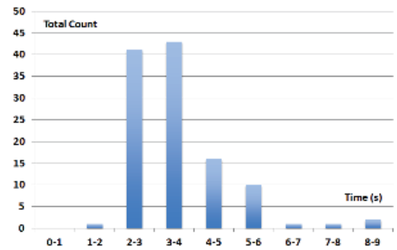

Figure 10. Histogram of time needed to generate the first heart rate estimation in City Defender.

Gold Miner

In Gold Miner, the lens covering action was used as a clutch rather than a trigger. As a result, the lens covering sessions in Gold Miner were fewer but had much longer durations than those in City Defender.

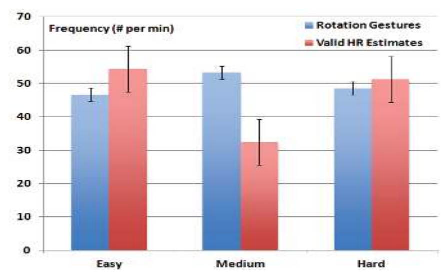

Figure 11: Heart rate estimation quality by difficulty levels in Gold Miner.

Figure 11 shows the impact of game intensity on numbers of rotational gestures detected, and the quality (i.e. number of valid estimates per minute) of heart estimates. Thanks to the strategic planning mechanism in Gold Miner, more intensive levels did not necessarily lead to more frequent rotational gestures and reduced heart rate quality. Although changing intensity level from easy to medium led to more rotational gestures, the number rotational gestures dropped when the intensity level changed from medium to hard. This is because participants started to change game playing strategy when the game intensity reached a certain level. Instead of simply moving the in-game character more frequently, participants started to devise a strategy with less frequent movement but better timing and planning.

DISCUSSIONS

The participants reported highly favorable experiences with LPG. When asked how satisfied with the games overall, the average rating was 4.25 ($\sigma = 0.60$) using a five-point Likert scale (5 = strongly favorable, 3 = neutral, 1 = strongly negative). Participants gave an average rating of 4.17 (σ =

[6] Defined as the number of covering sessions that generated heart rate estimates divided by total number of lens covering sessions.

[7] Defined as the total duration of covering sessions that generated heart rate estimates divided by the total duration of lens being covered by finger.

0.80) on the "fun" factor. The average rating was 4.67 (σ = 0.47) on ease of learning.

Sample comments from users include:

'I can get my heart rate after a relaxing game, which is better than barely using the mobile app.'

'I play games frequently and could easily fit a 'healthy' game in. Using an app feels like work'.

'If I do nothing but to wait for a long time, it's boring. But playing game is interesting.'

'I like City Defender. Because 'war game' is more attractive for me. And the difficulty of the game is reasonable, not trivial, but not extremely hard to make me frustrated.'

A few participants commented that the camera lens became a little bit hot after extended game play. This temperature increase was actually caused by heat generated by the LED flash of Google Galaxy Nexus. Interestingly, the flash in Google Nexus S did not have this heating problem. We recommend device manufacturers take the heat emitting ratio into account when choosing LED flash components. Turing on the LED Flash can improve the finger transparency readings in dark environments, but it is not required in indoor conditions with sufficient illumination. One user suggested the idea of changing the bezel of back camera to improve tactile feedback in game play - "*It is better to have a stopper like there are two stoppers on F and J on Query keyboard*".

Although not directly used in the actual game play, participants strongly preferred LPG designs with a small preview window of the back camera. Participants reported that the preview window improved the positioning of fingers on the camera lens when they were concentrating on the game screen. Interestingly, participants believed that the preview window improved their *perceived fluency* and *responsiveness* of game play.

Both non-gamers and frequent mobile game players appreciated the *fun* factors and the *depth* of LPG. In addition to the design of game workflows, fun factors also came from the alternation of input modalities (touch, lens-covering, motion sensing, and orientation matching) as well as the diversity of control paradigms (trigger vs. clutch). The effective mapping of input modalities and control paradigms to in-game challenges is a rich design space for creating engaging games. While increasing the quantity and frequency of enemies was an easy choice for improving the intensity and depth of game play, this approach had limitations on human motor control skills and can also have a negative impact on the quality of heart rate tracking. As demonstrated in the user study, it's important to design LPG such that proficient gamer can discover and leverage winning strategies that rely on *better timing* and better *strategic planning* rather than solely on *higher response frequency*. We hope the depth of LPG perceived by participants could translate to *sustained motivation* in a longitudinal setting.

Based on both quantitative analysis of game playing logs and qualitative feedback collected from the iterative design process and the formal user study, we'd like to recommend the following *preliminary* design suggestions for researchers and practitioners to who are interested in designing similar LPG.

- *Accuracy Guarantee*. It's imperative to design the game playing logic such that there are sufficient lens covering sessions longer than 2 seconds, ideally 4 seconds.
- *Satisfactory Intensity*. Enabling 10 - 15 lens covering actions per minute is a good balance between accuracy and intensity.
- *Alternative Strategy for Hardcore Players*. To achieve a good balance between accuracy and fun in high intensity levels, it's important to design LPG such that proficient gamer can discover and leverage winning strategies that rely on *better timing* and *long-term planning* rather than *higher response frequency*.

CONCLUSION AND FUTURE WORK

We presented LivePulse Games (LPG), a novel technique to measure users' heart rates in real time through serious games on unmodified mobile phones. Major contributions of this paper include: 1) We demonstrated the feasibility of real-time, non-invasive heart rate monitoring during mobile game play; 2) Through a 12-subject user study, we quantified the accuracy of LivePulse in both resting condition and game playing sessions; 3) We studied the impact of game intensity on LPG based heart rate monitoring; 4) We explored the design space and trade-offs of LPG through iterative design.

Our current research has only scratched the surface of LivePulse based heart rate measurement on mobile devices. For example, better algorithms, such as unsupervised Hidden Markov Models [9], can be designed to improve the signal utilization ratio. Output from built-in motion sensors can be leveraged as indicators to signal quality or even compensate noise caused by motions [14].

LPG are not intended for uninterrupted full day heart rate tracking for clinical use. Nevertheless, LPG can still open exciting opportunities on collecting, interpreting and using physiological signals. For example, physical exertion games by Mueller et al [19, 20] can be recreated as a software only solution after certain design changes (e.g. using the "clutch metaphor" for a walkie-talkie style speech interface, touching the camera lens of the phone mounted on the arm or belt to issue voice commands, or talk with other players).

According to a survey by comScore in 2013, 39% of time spent on smartphones was devoted to gaming [17]. Given the preference and popularity of mobile gaming, LPG have the potential to lower the tracking burden of the "quantified self" movement [11], where participants track physiological signals longitudinally, for both wellness improvement and self reflection. The pervasive monitoring of personal physiological signals in non-game settings, e.g. when using LensGesture apps [40], via technologies invented in LPG, can also provide interesting research opportunities for healthcare, personal well-being [5], and adaptive learning [15] in the future.

LivePulseGames are open source software released under BSD license. The current implementation can be downloaded from *http://mips.lrdc.pitt.edu/livepulsegames*. We hope LPG can inspire research prototypes and commercial products that change how people collect, understand, and consume physiological signals.

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