ULSAN NATIONAL INSTITUTE OF SCIENCE AND TECHNOLOGY

Master's Thesis

Exploring Design Opportunities for Technology-Supported Yoga Practices at Home

Hyunmi Oh

Department of Human Factors Engineering

Graduate School of UNIST

2019

Exploring Design Opportunities for Technology-Supported Yoga Practices at Home

Hyunmi Oh

Department of Human Factors Engineering

Graduate School of UNIST

Exploring Design Opportunities for Technology-Supported Yoga Practices at Home

A thesis
submitted to the Graduate School of UNIST
in partial fulfillment of the
requirements for the degree of
Master of Science

Hyunmi Oh

July 1st, 2019

Approved by

Advisor
Ian Oakley

ULSAN NATIONAL INSTITUTE OF SCIENCE AND TECHNOLOGY

Exploring Design Opportunities for Technology-Supported Yoga Practices at Home

Hyunmi Oh

This certifies that the thesis/dissertation of Hyunmi Oh is approved.

July 1st, 2019

signature

Advisor: Ian Oakley

signature

Professor Ian Oakley

signature

Professor Gwanseob Shin

signature

Professor Young-woo Park

Abstract

Yoga is a discipline that integrates mind and bodily exercises practiced for a number of health benefits. Although physical and mental health benefits from practicing yoga are well-known, people address time and cost as the primary barrier to incorporating yoga practices on a regular basis. A cost-effective solution to these limiting factors is adopting at-home practices. However, starting at-home yoga practices is difficult, especially for beginners, due to the lack of feedback on practitioners' performance. To tackle this challenge, we explore design opportunities for an interactive artifact that can effectively support yoga practices at home that can potentially replace professional personal trainers. Our approach for exploring this design space begins with a user study with a group of yoga practitioners in order to identify design requirements in a yoga practice environment. Based on the results from the user study, we provide some design insights for developing a feedback-based artifact for yoga practice in the home environment. Then, we exemplify how suggested implications can be applied to design with an illustration of a biofeedback-based mat for yoga breathing exercises. Beyond this, we inspect how the mechanism of biofeedback for breathing can be implemented by building a low-cost respiration phase detector to evaluate the quality of breath. The results from the study on the development of phase detector show per-user classifiers can identify respiration phases with mean F-scores of 0.69 for all poses and 0.78 for the baseline pose. This is an acceptable result acknowledging numerous momentary judgments are made to identify each breathing phase. Moreover, per-user classifiers for identifying three yoga poses show promising results, which can expand the application areas of the breathing phase detector. Through this series of context-driven exploratory studies, we demonstrate approaches to investigate design opportunities for technology-supported at-home yoga.

Contents

List of Figures

List of Tables

I INTRODUCTION

1.1 Background

Yoga is an increasingly popular discipline originated in India practiced for health and well-being through the adoption of bodily postures (*asana*), regulation of breath (*pranayama*), and meditation [1]. Despite its long-established goal in reaching a unified state of consciousness through a balance of mind and bodily practices, various styles of yoga have been introduced depending on the diverging priorities pursued by practitioner groups [2]. In other words, some groups show partial interest in the practices of physical postures rather than in the practices for inner development for reaching a higher state of being [2]. Perhaps, this is why yoga practice has been adopted to treat numerous physical and mental health conditions such as musculoskeletal pain, depression, anxiety as well as pulmonary diseases [3]. Aside from these benefits pertaining to medical conditions, some of the generally recognized benefits from yoga are physical fitness, an increase in cognitive function, and emotional well-being [4].

Although yoga is known for its potential health benefits, practicing yoga on a regular basis is challenging for many reasons. A review of empirical studies on yoga addressed the limiting factors for a regular practice among student population are time, cost, and the lack of practical information about yoga [4]. A simple solution to the conflicts relating to cost and time is adopting at-home yoga practices as suggested by experts [5]. However, there remains an unresolved yet critical problem to practices at home. When yoga practices are brought into the home environment, practitioners typically rely on instructions from experts and trainers on video tutorials. The lack of feedback on practitioner's performance in this environment consequently presents difficulties in learning to beginners, adversely affects people's self-satisfaction [6], and may even lead to loss of interests and motivation [7,8].

To tackle this challenge, we explore design opportunities for developing an interactive system that can effectively support yoga practices in the home environment. First, we identify requirements for designing an interactive system in this space by taking a context-driven approach for probing various concepts with yoga practitioners. Then, we suggest a design of biofeedback-based yoga mat for supporting yoga breathing practices at home based on the insights gained from the user study. Finally, we examine the feasibility of biofeedback-based training system for yogic breathing by elaborating how such a system can be implemented. Specifically, we design and develop a low-cost respiration sensing mechanism for detecting characterized phases of a breathing cycle.

From the preliminary user studies with yoga practitioners, we discovered three aspects of a yoga practice that our population is concerned about: breathing, posture, and motivation. Major findings from the second user studies show the preference over type of feedback modality largely depends on the level of expertise in yoga. In general, all practitioners preferred explicit feedback and guidance over implicit simple warnings. Apart from this, the results from the study on the development of phase detector show that per-user classifiers on all poses perform reasonably well, acknowledging numerous momentary judgments are made to identify each breathing phase. Moreover, per-user classifiers for identifying three yoga poses show promising results, extending applicable areas of the breathing phase detector.

The contributions of this work are:

1) design implications for feedback-based systems to support yoga practices in the home environment

2) a design of a biofeedback-based breathing training system based on findings from user studies

3) a demonstration of an exploratory work on respiration phase detection using machine learning classification methods

1.2 Thesis Statement

Biofeedback-based breathing training is a cost-effective and viable means to enhance the experiences of yoga practices in the home environment.

1.3 Thesis Structure

This thesis is structured in five chapters. In the first chapter, the background and motivation for this study are presented. The second chapter provides a review of related literature on breathing, respiration, and feedback. In the third chapter, user studies with 20 yoga practitioners are organized and described in detail. In the fourth chapter, steps taken to build a respiration phase detection sensor are explained. The performance of the respiration phase classifier is also analyzed in this chapter. This is followed by the last chapter of this thesis, which presents the conclusion and limitation of this work and pose a direction for future work.

II LITERATURE REVIEW

2.1 Overview

In this section, a comprehensive review of related works is presented. First, research works that involve yoga practice in HCI are surveyed. Next, a literature review on breathing studies is presented. This is organized into two different sections: one on breathing exercises for meditative purposes and the other in using breathing patterns as an input to a system. Then, studies on breathing sensing schemes are examined. In this part, contact and noncontact-based sensing methods are introduced, and the challenge that lies in our study context is addressed. Finally, this section ends with reviews on feedback strategies. We begin this final portion by clarifying the terms frequently used in this thesis. Then, the requirements for designing a successful feedback strategy are described, which is followed by feedback strategies employed to reinforce breathing exercises.

2.2 Yoga in HCI Studies

The research related to yoga practice in the HCI community is in an early stage as there are only a few exemplary studies. They are Eyes-Free Yoga [9], ExoPranayama [1], and Social Yoga Mats [10]. These studies can be characterized by the aspects of yoga they focus on. The first work focus on posture, the second on breathing, and the last on motivation. Eyes-Free Yoga [9] is an exergame specifically designed for visually impaired. The game helps users align their body by using only voice instructions and auditory feedback based on skeletal tracking with depth cameras. Studies on posture training include but are not limited to designing effective feedback strategies for other physical exercises and rehabilitation. For example, GymSoles [11] are insoles that provide visual and vibrotactile feedback on users' center of pressure to help them maintain a better posture while performing dead-lifts and squats. Another exemplary work is Physio@Home [12], a prototype that can possibly replace physiotherapist by guiding physiotherapy patients through exercises and correcting patients' movements with visual guides.

In another work, other important aspects of yoga, which are breathing and self-awareness, are investigated. ExoPranayama [1] is an interactive installation that physically displays the breathing pattern of a group of users with stretchable material. The last study mentioned positions their work on yoga in a social context. They developed Social Yoga Mats for senior citizens to spread awareness of physical activities within a peer group as a way to motivate themselves to exercise [10]. This study takes advantage of yoga as it is an exercise that can be done in a group class as well as alone at home.

All of these studies indicate that yoga is a physical exercise available and accessible to people of different ages and groups. These works also pinpoint that not a single aspect of yoga is remarkably essential in pursuing a practice.

2.3 Breathing in HCI Studies

In the field of HCI studies, breathing has been extensively investigated for its both voluntary and involuntary nature, ranging from the practice of deep breathing for reaching a relaxed state of mind to the manipulation of breathing for supporting the natural user interface.

2.3.1 Breathing Exercises for Self-Relaxation

Due to the strong correlation of breathing patterns with the state of mind [13], many researchers sought to enhance deep breathing practices based on the awareness of breathing. Breath awareness is a mindful exercise for cultivating and sustaining focused attention on breathing [13]. Breathing exercises in these mindful-based projects are implemented in a variety of forms with the use of tangible instruments for a physical representation of breathing patterns. A type of form factor that a growing number of systems utilize is the haptic interface that embodies shape-changing materials to simulate paced breathing patterns [14, 15]. Beyond developing small gadgets, some researchers developed interactive environments for immersive breathing experiences. Owing to the spaciousness of these instruments, breath regulating systems have been examined not only for a single practitioner [16, 17] but also for a group of users [1].

As there are many approaches to promote paced deep breathing, the feasibility of these designs also has been questioned. For that not all people have meditative spaces available for use, probing the distressing real-world situations in terms of physical context or setting draws attention. A few studies addressed this with context-relevant approaches for regulating breath in specific daily occasions. For example, [18] suggested and evaluated a peripheral breath regulation technique for desktop computer users. The study explicates how triggering the on-screen animation for a guide only when a user's breath rate exceeds a preset threshold is less distracting than giving real-time feedback about their current breath rate. Another study brings breathing exercise into common driving scenarios and illustrates subtle and easy to engage in-car interventions by comparing the guidance system based on vibrations on the car seat and voice commands [19].

2.3.2 Breathing as a Control Mechanism

Another aspect of breathing that attracted many HCI researchers is the characterization of breathing patterns for the natural user interface. Some iconic examples that use variations in breathing patterns as control mechanism are breath-controlled games like FlappyBreath [20] and ChillFish [21]. In these games, user's respiration phases such as inhalation and exhalation drive the player upward and downward. Another exemplary work is Broncomatic [22] in which the user's breathing patterns and speed are mapped into the direction and rotational speed of the bucking bronco ride, respectively. Building on these studies, another work BreathVR [23] characterizes the quality of user's breath into four categories (e.g. gale, gust, waft, and calm) to initiate certain player actions in a VR game. Furthermore, breathing patterns have been suggested for intimate communication mechanisms to share emotion. An exploratory study indicates that breathing is closely related to emotion on an evolutionary perspective and describes how they utilized features of breathing such as pace, amplitude, and variability of breathing patterns to derive a lexicon of ten breathing traits and the corresponding emotion [24].

Previous studies indicate breathing can be voluntarily managed and breath can be marked by the duration and stability of a breathing pattern. Building on this concept, we believe that we can improve the quality of breath through sufficient training. To address the viability issue, a context-driven approach is taken in an aim to design a system that can assist users to learn a balanced breathing technique in a yoga practice environment. We examine the quality of diaphragmatic breathing specifically by segmenting a complete respiration cycle into four phases: inhalation, retention following inhalation, exhalation, and retention following exhalation.

2.4 Respiration Sensing

The foremost prerequisite for implementing an interactive system to support breathing training is a reliable breathing detection scheme. Over the past years, numerous contact-based and noncontact-based respiration detection approaches have been proposed.

2.4.1 Contact-based Methods

The contact-based respiration sensing methods require sensors or instruments to be in physical contact with the human body. A common type of contact-based method utilized in HCI research is the estimation of breath per minute (BPM) from physiological measurements such as Electrodermal Activity (EDA) and Heart Rate Variability (HRV). These measures captured from electrical properties of the skin and electrocardiogram [19, 25]. Other contact-based sensing methods estimate breathing from changes in sounds [26], airflow [27, 28] or chest and abdominal movements [19, 26, 29, 30] caused by respiratory motion [31]. A critical disadvantage of these approaches is the physical attachment of the instrument onto the body.

2.4.2 Noncontact-based Methods

The noncontact-based respiration sensing methods are non-invasive for that these do not require instruments to physically be in contact with the human body. These methods are largely based on wireless sensing by utilizing radar [17, 32] and infrared imaging technologies [33, 34] to extract respiration signals [31].

Although these approaches are well-received by users for their unobtrusiveness, their main limitation is the vulnerability to bodily movements and changes in the surroundings. In other words, radar and camera-based methods perform well only when users stay still because the motion they voluntarily or involuntarily make consequently corrupts the necessary signals for breath rate estimation [31]. This is a critical defect for any respiration detection system when evaluating the performance in terms of reliability and accuracy.

2.5 Feedback Strategies

The chief purpose of our system is to aid novice yoga practitioners in learning and training equal-breathing technique in their asana practices. Our research interest specifically lies in the domain on feedback strategies for breath regulation in a learning perspective. Therefore, we first clarify the meaning of the term feedback used throughout this thesis. Then, a brief review of the design of successful feedback strategies in a learning perspective is presented. This is followed by a review of HCI studies on breathing in terms of feedback.

2.5.1 Terminology: Guidance, Feedback, and Intervention

The terms guidance, feedback, and intervention may not be used interchangeably in general. In the HCI community, guidance is help or advice in any form that tells the user what to do and feedback is an outcome that shows the user’s performance on a given task. These are different in that former is given before a subject takes an action or performs a task while the latter is given as a result of the action taken or the task that has been performed. When this course of events is considered in a different point of view, guidance may be provided as feedback. For instance, when a user performs poorly while using a system, whether it is due to the user's ignorance of proper system usage or the difficulty of a task, providing specific instructions to help a user do better is more effective than popping up an error message. Here, the instructions given to the user are guidance, but it is also feedback since it is provided as a result of an action the user has taken.

Intervention is rather a flexible term that can encompass both definitions of guidance and feedback. It is defined as interference during a course of events to improve a situation [35]. In other words, its definition does not specify the point in which the interruption occurs during a course of events. Following this perspective, the terms intervention, feedback, and guidance used in this thesis convey the same meaning, which is any type of intervention provided as a response to an action taken by the system user.

2.5.2 Design of a Successful Feedback Strategy

Augmented feedback is acknowledged to be effective in general especially in preserving user interest [8] as well as in enhancing learning performances [36]. Yet, there still is an ongoing controversial discussion about which feedback strategy is most beneficial due to the complex nature of its assessment [8]. For instance, a study denotes that while real-time feedback on user performance is helpful in balance training than no feedback for both young adults and elderly, direct visual feedback may provide no other benefit because players are inclined to focus on the outcome of their movements rather than the task itself [8]. In addition, the study remarks that the senior users reported experiencing fatigue as they found the visual feedback elements cognitively demanding [8]. Similarly, another study presents a comprehensive review of numerous literatures on the effectiveness of digital game-based motor learning with immediate feedback regarding the characteristics of learners such as age, weight, gender, and the types of learning outcomes such as motor skills, fitness, motivation, attitudes, and knowledge [37]. Thus, in order to design a successful feedback strategy, the following design criteria including the type (explicit or implicit), intervening period (concurrent or terminal), modality (visual, auditory, haptic or combination), frequency and intensity of feedback should be considered appropriately in relation to the purpose of the system and usability requirements for end-users.

2.5.3 Interventions to Enhance Breathing Exercises

A vast number of projects in HCI community pertaining to breathing seek a broad goal, which is promoting slow breathing for relaxation. This can be achieved in two ways: either by reflection or entrainment. Reflection is when the users' breathing pattern is projected onto an external medium so that it can be easily perceived. Reflection by seeing, hearing, or feeling their own of breathing pattern raises users' awareness of breathing. This type of method is often adopted to responsive environments in the form of interaction mechanism, where users' breathing patterns activate and manipulate surrounding architecture. For example, a mediated space called Breathing Room [17] features a living wall and light effects that pulsate with breathing pattern extracted from a radar sensor. Other examples include ExoBuilding [16] and ExoPranayama [1]. In these systems, the fabric of a tent-like structure stretches and contracts in accordance with the rise and fall of users' abdominal breathing. As exemplified in the works mentioned, mirroring of user breathing patterns through apparent changes in the physical properties of the external medium such as shape, height, and volume help users attentively manage their breathing. It is believed that this type of interaction also allows users to gain greater control of their breathing [1].

On the other hand, entrainment is when users are synchronizing their breathing to a paced rhythm shown on a display. This process is attributed to our natural tendency to synchronize internal rhythms to that of an external stimulus [38]. The feedback designs based on entrainment make use of perceptual changes in the sensory modalities (e.g. visual, auditory, haptic, and multi-modal). For visual feedback modalities, movement of animated object or characters [20, 21, 38, 39], as well as variations on color properties such as hue and brightness, have been utilized. An illustration of this approach is mapping the user's respiratory state to the vertical movement of the animated player in mobile games such as ChillFish [21] and FlappyBreath [20]. Another example that relies on visual perception is BioFidget [25]. BioFidget uses the spinning ring for displaying different color channels and hue range to show differentiate phases of a breathing cycle and the quality of exhalation. Auditory entrainment is used for guiding a paced breathing by modulating frequency and amplitude of non-speech audio like a sound from nature [40] or white noise [41]. In addition, there are projects that incorporate haptic interfaces. In these works, temporal patterns of vibrations [19] and volume changes of an inflatable gadget [14, 15] are suggested for conveying inspiration and expiration by implicitly relating subtle changes to respiratory motion of lungs. More efforts have been made to use multi-modal approaches. For example, BrightBeat [42] adjust both screen brightness and white noise volume simultaneously to guide target breathing pace.

III User Study

3.1 Overview

To explore design opportunities for an interactive system to support yoga practice at home, a two-step user study was conducted. The main objective of this study is to derive key features and the requirements for a context-relevant design. The first phase of this study began with semi-structured interviews investigating end-users and the usage context. The second and the last phase of this study uses speed dating method [43] to rapidly explore and address design opportunities.

3.2 User Study Part I: Investigating the Usage Context

3.2.1 Aim

The aim of this user study is to explore the design space for a technology-supported coaching system for at-home exercises with a specific goal in understanding the user and the context by examining a specific exercise group, the yoga practitioners and their experience.

3.2.2 Materials and Methods

Semi-structured interviews were conducted with 11 yoga practitioners. All interviewees were female with mean age of 23.91 (SD = 1.76). The interview questions are mostly open-ended questions asking practitioners about their own experience. The questions cover their level of expertise, the motivation for practice, the place they choose to practice, the materials or references they use during their practice, their experience with free and/or paid apps, as well as their experience with exergames such as Wii Fit[1] and Your Shape: Fitness Evolved[2]. Aside from these basic questions about where and how they prefer to practice yoga, interviewees were asked to prioritize the aspects of a yoga practice. For instance, some may consider pose alignment over breathing stability while others may not. Like this, the interview questions can be answered freely based on their opinion from their own experience; therefore, there are no right or wrong answers. Before proceeding with the interview, the aim and

[1] Wii, Nintendo Co. Ltd, Kyoto, Japan. https://www.nintendo.com/games/detail/wii-fit-u-bundle-wii-u/

[2] Xbox360, Ubisoft, Montreuil, France. https://marketplace.xbox.com/en-HK/Product/Your-Shape-Fitness-Evolved/66acd000-77fe-1000-9115-d8025553084f

scope of the study were explained, and all participants were ensured that they are not being evaluated on their responses.

To account for instructor's point of view, semi-structured interviews with two certified yoga instructors were conducted. The questions center around instructor's work experience, class structure and curriculum, major concern among novice learners, strategy for encouraging learners, and know-how on adjusting difficulty level in a group practice. All interview responses except for those from professional instructors were audio recorded and transcribed.

3.2.3 Results and Discussion

The transcribed interview responses from yoga practitioners were analyzed through open coding [44]. Open coding is an analytical process frequently employed in qualitative research for data analysis. In this procedure, the transcribed interview scripts are segmented into meaningful pieces of expression [44]. These chunks of expressions are then assigned labels or codes to find overarching themes and concepts. In this user study, open coding was performed by reading through the transcript line by line.

The result of open coding shows three concepts to consider in a yoga practice: posture, breathing, and motivation. All of these categories are critical in yoga practice. Both posture and breathing are equally important aspects of yoga by its definition, and motivation is an essential factor in sustaining the practice or any other exercise on a regular basis. The codes that relate to learning and maintaining the pose are grouped into the concept posture. Similarly, the codes that relate to learning and maintaining breathing exercise are grouped into breathing. All codes relating to recommendations or regulations for the best physical effects and benefits from practice are grouped into motivation.

The codes grouped under posture are detailed instruction, key points for a specific pose, level of difficulty, physical feedback, and duration for holding the pose. An example of expression coded as detailed instruction is when an interviewee described her situation in which she was not able to keep up with the instructor's pose due to a blind spot. P5 compared how her yoga practice at home and yoga school differ: "At the yoga school I have the instructor right in front of me, so it is easier to understand what is going on. But when I practice at home, I need to have set up the small 2D screen. I don't find it satisfactory because I cannot get instant feedback." Majority of the interviewees who have practiced yoga with online tutorial video clips reported similar problems because the instructions are given in one-way communication. In a similar fashion, many interviewees who identified themselves as a novice practitioner explained their struggle in finding the key points to making a perfect pose. P3 explained, "the only concern I have in terms of poses is how can I not perform the poses in a wrong alignment because I know it can be harmful to my body. So, I basically want to know the key points and cautions for a pose." Moreover, individual differences in flexibility and balance greatly affect body alignment and posture. Considering individual differences, the level of difficulty in a pose can be adjusted in a yoga class, but these are usually not considered in video-based tutorials due to one-way communication. For example, P7 reported, "I am less flexible in posterior muscles of my thighs, so I struggle in poses that require these muscles even when the poses are at a basic level." When a practitioner is having difficulties in a yoga class, "the instructor slows down with the pace and shows variations to the pose" as P9 and P10 mentioned. Another difficulty that arises from one-way communication is the absence of physical feedback. For instance, when a practitioner performs a pose improperly, yoga instructors physically help the practitioner to correct the posture. P8 stated "I started yoga by watching a popular video tutorial, but the video is inefficient since it cannot tell you how you're doing" and explained, "there's this ah-ha moment when I do something wrong and the instructor comes along to fix my pose." This, however, is not possible when practicing alone at home. Lastly, interviewees identified maintaining a pose for a certain amount of time as a challenge. For some, sustaining a pose is difficult because their body alignment is not balanced while others indicated they do not push themselves only when they are counting time by themselves because no one else is around to watch after them. P2 described, "I thought I could do it [sustaining the tree pose], but I could not sustain the pose for long because I was wobbling." P4 noted, "When practice alone with video clips, I skip over parts that seem to be difficult." The holding time for a pose seems to be an apparent problem, especially in a group class as many interviewees explained how they tend to ignore instructor's verbal cues to maintain their own pace. P11 explained, "I think I have established my own style from practicing alone for a long time because I like keeping up with my own pace." Moreover, a desire for accurate counters in the practice was shown as P8 noted: "instructors are not accurate since they are not computers."

The codes grouped under breathing are about learning breathing technique, attentive breathing, and breathing pace in relation to the pose. As an example, P4 expressed "breathing is mentioned many times in videos and online tutorials, but it's really hard to know how to do it properly by just listening to the instructions. I really have no idea how to incorporate breathing technique while performing the poses." This shows the difficulty in learning the breathing technique and in maintaining a stable breathing pace. Almost all practitioners found learning a breathing technique difficult, especially if they are a beginner level practitioner. The possible cause for not being able to sustain a stable breathing pattern is either they care less about breathing or their full attention is in performing and maintaining a pose. P9 noted, "having constant guidance for breathing would be helpful since I may unconsciously give up on retaining a stable breathing pace."

The codes grouped under motivation are about the assessment of poses for best physical benefits on the body after the practice. Here, motivation is linked with pose assessment because they are closely related. The interview responses show the greatest motivation for practicing yoga regularly is being able to visualize or feel the physical benefits. For example, P5 stated, "knowing which body part most benefits from a pose is helpful because it is a direct achievement from doing any physical exercise." Participants explained these parts differ by poses and knowing them is important to check whether they are making the pose correctly or not. P6 described, "I feel like I am doing something wrong when I do not feel the tension from a pose. I often ask the instructor whether I should feel the tension in this part of the body or not." Some others pointed out that they like focusing their attention to the tensed parts of their body when practicing yoga as the tension brings personal satisfaction. P6 mentioned, "when the instructor explains the benefits of the pose, I tend to focus my attention on the specific body part. It makes a big difference in my attitude and satisfaction even though when I am performing the same pose." Aside from this temporary feeling of satisfaction, the majority of yoga practitioners seek long-term effects on their body. The reason behind this is all practitioners were aware of the fact that yoga is not an intense fitness exercise that brings about apparent physical changes to the body in short-term.

3.3 User Study Part II: Navigating the Design Concepts

3.3.1 Aim

The aim of this study is twofold: 1) to gather practitioners' opinion about technology use for yoga practice and 2) to examine preferred feedback modalities in a typical yoga practice environment.

3.3.2 Materials and Methods

The material used in this part of user study is a set of storyboards generated based on the findings from the previous step. The purpose of using storyboards is to help participants grasp the idea of the concept that they are unfamiliar with. The very first step to creating storyboards is setting a persona. By definition, a persona is a fictional character created to represent a possible end-user for the designed artifact [45]. In this study, a female yoga practitioner named "Anna" is set as a persona. The primary role of Anna is to better illustrate the use of technology and feedback in realistic yoga practice scenes. This helps interviewees understand the given context when they are asked to freely express their opinions on how well the technology may be received.

With Anna as the main character practice yoga in each scene, nine different storyboards have been generated. These scenarios interweave various types of devices from smart glasses and smartwatches to outlandish sensor patches and various feedback modalities including audio, visual, tactile, and multi-modal. The different combinations of devices and feedback modalities are intentionally illustrated in a strange way at times to provoke participants to think beyond these devices and modalities. This kind of illustration can also benefit from testing the extremes in devices and feedback modalities that can be well-received in the study context. A storyboard on breathing training is shown in Figure 1. Full storyboards can be found in Appendix A.

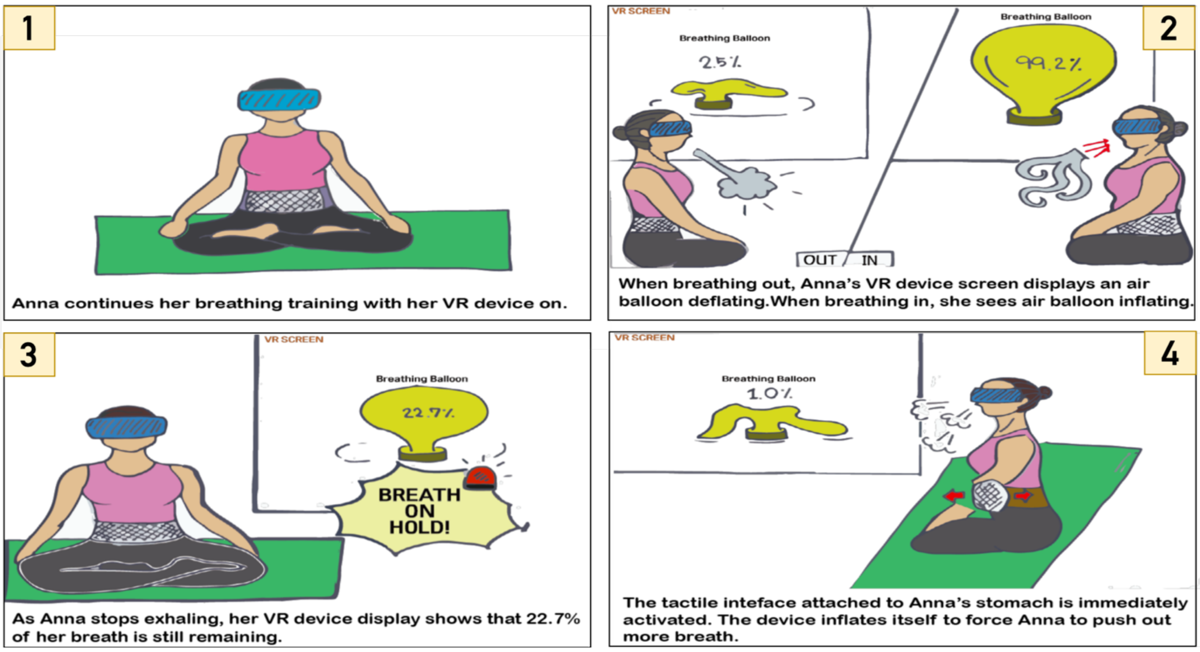


Figure 1. A storyboard generated from breathing training scenario.

In the second semi-structured interviews with another ten yoga practitioners aged between 24 and 29 ($M = 26.40$, $SD = 1.51$), nine sets of storyboards were quickly shown using speed dating method. Speed dating is a design method presented by a group of researchers for rapidly exploring concepts of a system without actually implementing the artifact or application [43]. The greatest advantage of this method is numerous design concepts and potential risk factors can be examined in a timely manner because it does not require any technological implementation. We utilize this method to explore design opportunities for a feedback system in a yoga practice environment.

The informal interviews with speed dating took place in a café located on the campus. The purpose of the study was explained to the participants prior to the interview. This is to ascertain the interviewees that the goal is not on validating a demonstrated concept so that any negative and pessimistic views are also valuable and appreciated. The order of storyboards was counterbalanced. All participants were encouraged to freely express their honest feelings toward any idea or concept presented in the story. They were allowed to interrupt the interviewer in the middle of the story if they had any questions. At the end of each concept, they were asked a set of prepared questions on each of the concepts. For the storyboards on breathing training, questions were asked about the parts the practitioners liked the most, their opinion on the numerical representation of breathing, physical assistance for breathing, symbolic representation of a breathing cycle with a balloon, and the wearability of VR device. The key concepts inspected in each storyboard are summarized in Table 1. When all of the concepts are shown, participants were given a summary map of nine storyboards as shown in Figure 2. They were asked to rank the concept from most favorite to least favorite and provide a short brief reason for their choice. All interviews were audio recorded and transcribed afterward.

Table 1. Key concepts and ideas inspected in each storyboard.

BREATHING	Breathing Training	Breathing Awareness	Holding Time
	Numerical representation Wearability of VR device Physical assistance Symbolic representation of breathing cycle	Explicit voice commands External source Robot Humidifier-looking device	Ambient lights Ball lamp Implicit notification using music (on and off) Wearability of wristband
POSTURE	Wrong Posture Alert	Posture Guidance	Harmonious Learning
	Mat vibration Siren lights Patch sensor with electric jolts	Visual guidance Noise from speakers	Adaptive environment Mat display Tactile mat Sound of nature Metaphorical representation
MOTIVATION	Physical Effects	Self-Assessment	Game Design Elements
	Color codes for tensed muscles Wearability of smart glasses Realistic visualization of muscle activity	AR mirror matching Playback with evaluation Daily progress reports Personal record management	Competition Virtual rewards Goal-oriented practice Practice evaluation and scoring

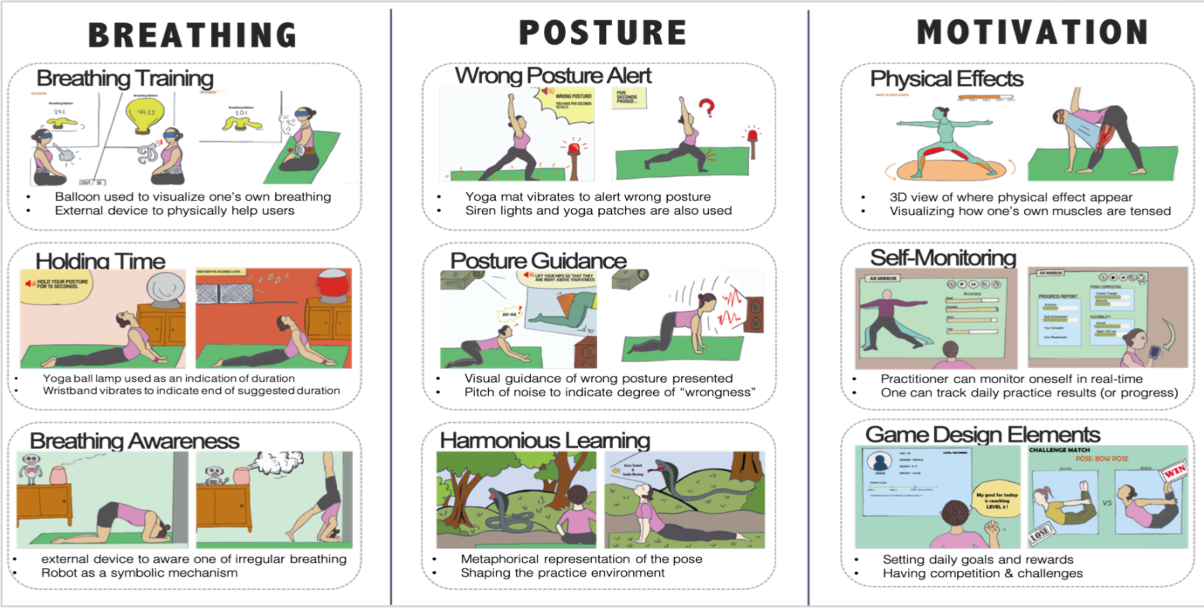


Figure 2. Summary map of all storyboards provided to participants for ranking after speed dating.

3.3.3 Results and Discussion

The transcribed interview responses from yoga practitioners were analyzed through open coding in the same manner as the first interview. A difference from previous interview is the responses on specific concepts and ideas are classified into one of the following three criteria: positive, negative, and neutral. These results are summarized by each theme below. This process is done in a software for qualitative analysis called ATLAS.TI as shown in Figure 3.

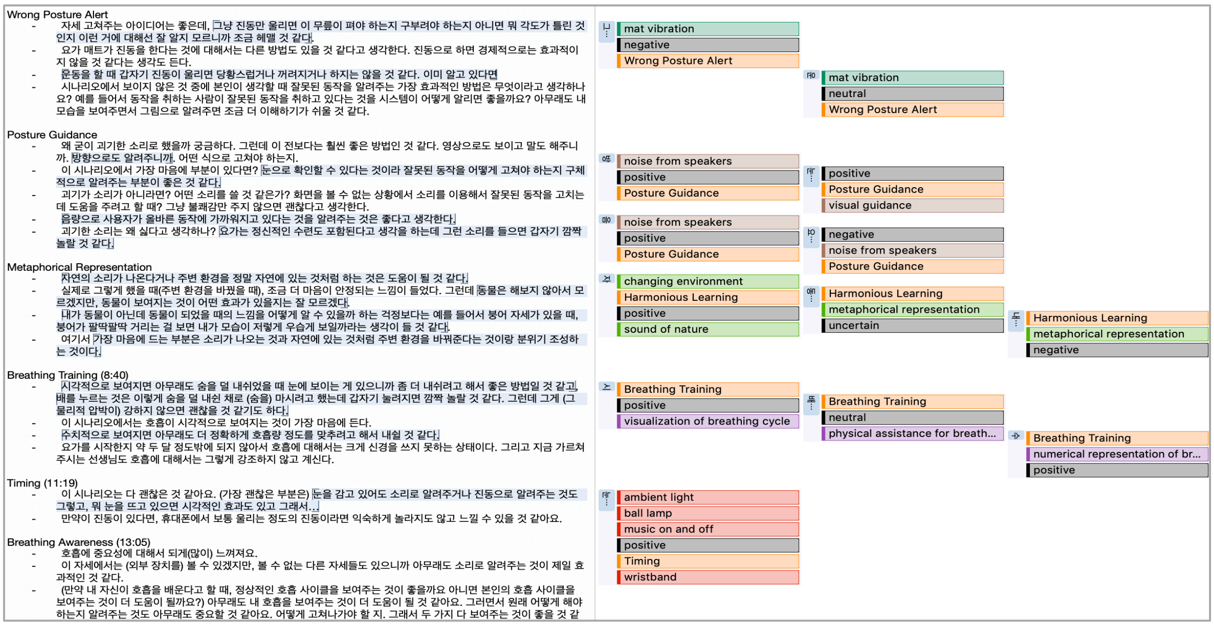


Figure 3. An example of how transcribed interview scripts were coded using Atlas.Ti. The left side of the screen shot shows the transcribed interview from P5. On the right side, the codes linked to each quotation are shown.

Breathing Training

For the breathing training scenario, there are two visual modalities and a tactile modality for providing feedback. Overall, yoga practitioners' opinion on visual feedback for breathing guidance was positive. Majority of novice practitioners found the symbolic representation of breathing helpful because breathing is something you cannot clearly see and grasp from a demonstration. P8 believes inflation and deflation of a balloon for illustrating respiration cycle are helpful as he "can easily associate inspiration/expiration from the illustration." Some advanced practitioners, however, expressed no interest in this idea as they prefer to practice yoga with their eyes closed and relying solely on auditory instructions. For instance, P9 mentioned "visualization of breathing cycle will be helpful when you want to learn the breathing technique," but noted, "I prefer to practice breathing with my eyes closed." The idea of showing a numerical representation of breathing was received positively in that numeric values are easier to perceive in comparison to an abstract representation and that it can indirectly encourage practitioners to breathe more properly. P7 elaborated why she believes numerical representation is very helpful by saying, "it can tell you the endpoints to each respiration phase, which is hard to know from the shape of the balloon." In contrast, some practitioners strongly disliked the idea for it may cause practitioners to become calculative and force them to achieve a better accuracy like a game, which contradicts the ultimate goal of yoga. P4 exemplified his response toward the idea: "I think it would be fun, but I will surely become more calculative. Though I know that relaxation is very important in breathing practices, I will be in a hurry with my pace when I see 22 percent of breath left in my balloon."

Opinions were divided over having physical assistance to help with breathing training. The physical assistance is provided by an inflatable tactile interface attached on Anna's stomach. Some people were against the idea because it may be too frightening and distressful. Some were indifferent because they have never been exposed to this kind of technology, but if the force or the pressure is not too hard, they thought it would be interesting. For example, P2 thought "it is okay since I am aware of the physical device and the feedback," but P3 believes "it would be frightening if the device forces me when I try to inhale without completely exhaling the amount of breath the device expects me to exhale." Some others thought it would be helpful to beginners. The overall opinions are positive in nature the device tells you what to do.

Every yoga practitioners who participated in this interview disliked the idea of wearing a VR device during a yoga practice. From their experience, they explained wearing VR headset is cumbersome, discomforting, and even nauseous. They also explicated that this idea does not go well with breathing training since breathing practices are meant to relax people not weary.

Breathing Awareness

Breathing awareness scenario features two audio-visual feedback modalities, one explicit and the other implicit, with external devices. External devices are tangible artifacts that appear in the scene but not physically in contact with Anna. In this scenario, Anna is practicing a difficult yoga pose that requires her full attention and a humidifier-looking device and a robot attempt to help Anna raise awareness of breathing.

Overall, practitioners were against adopting these devices in their practice. All practitioners mentioned they would not be able to notice the change around them when they are performing a difficult pose. P9 pointed out, "when we perform difficult pose that we forget to retain a stable breathing pace, there is no way we notice any changes in the external devices." Also, they pointed out letting one know that one's breathing cycle is unstable does not help the user at all. This may rather be frustrating since the practitioner does not know how to stabilize their breathing pattern. P10 said, "I will not buy the robot because the device does not guide Anna back the stable pace but only tells her that something is wrong." Therefore, in this circumstance, they prefer specific guidance over a simple alert.

Holding Time

A variety of feedback modalities including visual, audio, and tactile appear in the scenario related to posture and breathing holding time. First, practitioners' opinion on visual modalities were mostly positive. They liked visually and indirectly informing how much time has passed when holding a pose is useful. P5 exemplified how she would use this in her practice by saying, "I would use this timing function because my willingness for holding the pose decreases when I practice alone." However, interviewees pinpointed that there is no need to have two visual modalities and that one is enough. For example, P4 mentioned, "There are so many notifications in this, and I think one is enough." They prefer visual feedback that can ambiently notify them of the time elapsed and did not like having to stare at an artifact in a fixed position to obtain any information.

Opinions over auditory feedback with switching background music on and off were diverse. Some people disliked the idea saying that it would be disturbing. P6 said, "When I am totally engaged in the practice, I can only rely on sound for anything else. So, I always have music playing in the background." She also suggested, "there are other ways you can use sounds for notification in yoga rather than pausing the background music." Others were indifferent but suggested using volume changes instead because they prefer to practice with background music on. The rest liked the idea because it is feedback that can be perceived when their eyes are shut.

On the idea of having tactile feedback from a smartwatch, participants' opinions were divided again. Some people were strongly against the idea identified himself as an advanced yoga practitioner and said, "maintaining a posture for a long time is not bad for you." Other practitioners mentioned that constant vibration on the wrist would be disturbing because it is the feedback you cannot ignore while performing a pose. People who liked the wristband vibration feedback explained their reasons as most feasible and most appropriate for notifying the holding time. P3 said, "if the vibration is as gentle as the one from a smartwatch, I would not be frightened since I am accustomed to it." Participants also suggested using this idea to help practitioners maintain balanced poses for an equal amount of time. Other than this, the wearability of a wristband during practice was never an issue.

Wrong Posture Alert

The expression wrong posture was most controversial in this scenario. Many advanced yoga practitioners were confused by the expression and often asked what we meant by a wrong posture. To yoga practitioners, there is no such wrong posture as there is no universally correct alignment. They believe the factors that harm practitioners are not doing the wrong postures but overstressing their body beyond their individual ability.

In this scenario, there are an auditory and two tactile feedback modalities. The first feedback concept that almost every practitioner disapproved was vibrating mat. This was received as disruptive, frightening, and useless. P5 explained, "I would not know what I have done wrong if the mat suddenly vibrates so it will be frustrating." Similarly, P4 specified that "it would be rather helpful if the system tells me what exactly I did wrong and the way to fix it." Some participants also noted vibration can consequently disorient postures.

Another tactile feedback concept, electric jolts from patch sensors, was well-received by the majority of practitioners. Although some were against wearing sensors during a practice, many found this feedback beneficial. P7 stated, "it would be useful to beginners since it directly notifies you which part of your body is misaligned." Participants elaborated they are aware of wearing sensors is uncomfortable and inconvenient, but they would still buy the idea due to the aforementioned reason.

Posture Guidance

In this scenario, only two feedback modalities are used: graphical guidance to help a practitioner correct their alignment and loudness of noise from speakers to inform how far a practitioner's pose is from the desired. Actual practitioners' opinion on both of these feedback concepts were divided. Many practitioners accepted that knowing how close their pose is to expert's is helpful and may motivate them to do better. However, they took graphical guidance as an instantaneous correction that is not sustainable. In other words, they were afraid that they would rely on this feedback if they are available at all times. For instance, P6 recalled her practice at a yoga class, "I remember my instructor repeatedly asking us (practitioners) to feel their body and find what is best for us. I am afraid this function may consequently drive people to fit their body to a guide without getting to know their own body." Noise from speakers was received well for its usefulness in directing the users to modify their pose. However, the noise itself was received as frustrating, frightening, and startling.

Harmonious Learning

The principal theme that we aim to explore is how practitioners receive bringing a yoga practice into a nature-friendly environment. Five concepts are examined in this scenario: three on visual, one on auditory, and the other on tactile modality.

For visual assistance, we make use of displays and show how a practice environment can switch to a scene in nature. Some people believe creating such an atmosphere may increase user engagement, but P2 said she is uncertain about the idea "because she could not imagine how it would actually feel like." Metaphorical representation is used to illustrate the instructor's pose as an actual animal. Opinions were mostly uncertain and negative on this idea. P5 stated, "I like the changing environment because I would feel more relaxed in a nature-friendly environment, but I cannot imagine myself performing a cobra pose by looking at an actual cobra. I mean, a cobra has no arms." An instant reaction from P3 was "my only concern about this is would I look that humiliating in that pose?" Others indicated that they would at least use this once for fun, but not sure about a continuous use.

In the scenario, the sound of nature is played on the background without a specific purpose. This means the sound serves no role as an indicator. Nevertheless, the majority of participants admired this idea because it makes them feel comfortable and it is easy to relate the sound with a peaceful mind.

To many practitioners, having tactile feedback from the mat like the roughness of grass seems unnecessary. For example, P5 elaborated "tactile sensation may feel discomforting especially when I imagine myself having to kneel down on the rough grass." Few others stated they have no opinions and thoughts about this idea because they cannot imagine such.

Physical Effects

In this scenario, we survey practitioners' preferences for the type of feedback for instantaneous physical effects. We acknowledge yoga is not a practice that results in short-term apparent physical changes on the body. We only anticipate ways to foster a feeling of satisfaction while and after exercising. For example, yoga practitioners in the previous interview mentioned that they feel satisfied when they feel the tension in certain body parts while practicing. This is replicated in this scenario with color-coded tension in body parts. For example, body parts that should predominantly be tensed would be shaded in red while parts with mild tension would appear in lighter colors. All practitioners responded positively to this idea regardless of their level of expertise, showing a willingness to adopt this idea in their practice. P10 mentioned, "this is the best idea so far because sometimes I wonder why I am doing this pose or what is this posture good for?" Another concept investigated in this scenario is a realistic visualization of muscle activity. All practitioners were against the idea and received it as gross, scary and useless. P8 explicated, "I personally like the idea, but to be honest I don't think it'll be helpful at all."

Regarding the wearability of smart glasses, one of the participants perceived smart glasses as accessories like jewelry she would remove before starting her practice. Other practitioners were not bothered by wearing smart glasses because they received the device as regular glasses.

Self-Monitoring

The four concepts inspected in this scenario are AR mirror matching, daily progress, personal records management and playback with posture evaluation. AR mirror matching is when Anna modifies her posture to match the one shown on a virtual screen, an AR mirror. Practitioners' opinion over this was dependent on their level of expertise. While advanced practitioners pinpointed this idea violates their goal of practice which is to concentrate on oneself, beginners believed monitoring oneself on a mirror best suits the needs of practitioners. An advanced practitioner P7 said, "if I were to use this function, I try to fit myself into the reflected image on the mirror, instead of concentrating on the tension I feel in my body." On the other hand, a novice practitioner explained she likes the idea because "seeing how close I am to the perfect pose on the mirror would be really helpful in improving my posture."

All practitioners were pleased about reviewing daily progress reports and keeping personal records for their practice. Some practitioners emphasized that they would always use this function if it is available. P3 explained, “since yoga is not an intense exercise that brings about physical changes in short-term, I would enjoy seeing the daily progress like this.”

On the other hand, playback with posture evaluation was not received well for the following reasons. First, practitioners stated it seems like a function for entertainment. Second, they strongly dislike numerical scoring and evaluation of their pose. Last but not least, they elaborated that it would be time-consuming to watch all of them.

Game Design Elements

The last scenario explores game design elements in yoga practice. Four concepts under consideration are competition, goal-oriented practice, posture scoring, and virtual rewards. Practitioners’ opinion over competitions were divided among gender groups. Male practitioners found it interesting to compete with others to make a better pose while female practitioners found it a bit embarrassing. A male participant P8 said, “competitions and rewards could be a great motivation for exercises like any other exercise mobile apps. I wish there are more components that can give us a feeling of achievement.” A female participant P9 indicated, “I probably would not use this because I do not like sharing how I look in the pose with others. Some specified it may depend on the goal of practice. For instance, if what you want to achieve from practice is peacefulness you would better keep yourself away from the competition. P1 specifically said, “even though I am a beginner, I think elements like competition violate the power of yoga.”

The goal-oriented practice was received positively in general. Practitioners’ thoughts on posture evaluation were generally positive for that this may be interesting. P2 mentioned, “I like how you can set up daily goals and having the system to evaluate your achievement for the day.” However, there were practitioners who could not relate to movement evaluation with numerical scores.

Opinion over having virtual rewards were diverse. For some virtual rewards had no significance while others said it is pleasant to get virtual rewards. For example, P9 mentioned, “I don’t see the merit of receiving virtual rewards” while P4 suggested, “why can’t we have real rewards like the money? I think it would be very motivating.”

3.4 Design of Biofeedback-based Yoga Mat for Breathing Training

3.4.1 Design Implications

We identify following requirements for feedback design to support yoga practice:

- Practitioners' preference over auditory or visual feedback largely depend on their level of expertise in yoga.
- Regardless of expertise in yoga, practitioners prefer visual feedback for learning abstract concept like breathing.
- Poses should account for individual differences and there is no such alignment or posture that is universally correct.
- Feedback should not interrupt the practice and should be disregarded easily.
- Feedback should not be continuously provided; should be provided only when the practitioner is doing something wrong.
- Feedback should not direct practitioners' visual attention to an external source that is irrelevant to the practice.
- Feedback should explicitly guide practitioners so that they can easily find their ways out of undesirable circumstances.

3.4.2. Proposed Design of Biofeedback-based Yoga Mat

Based on the above requirements, we propose a design of biofeedback-based yoga mat specifically for beginners to support breathing practices. We refer to a specific breathing technique called *sama vritti*, which emphasizes the practice of equal-ratio breaths that are evenly balanced in length.

Initial Prototype Design

Our initial prototype design provides audio-visual feedback for training *sama vritti* in a seated posture. The yoga mat prototype senses a user's breathing pattern through a piezo-electric sensor which is attached to a clear sanitary mask as shown in Figure 4. The piezo-electric sensor placed beneath the nostrils detects inhalation and exhalation from a preset threshold. When a user's breath per minute (BPM) is measured during the first three minutes of the practice, the mat provides an appropriate visual guide with LED strips attached to the sides of the yoga mat. Figure 5 is a diagram that shows how the visual feedback is designed. The status of LEDs in the strip changes in relation to the diameter of the center ellipse. Blue dashed lines indicate the boundaries of horizontal diameter of the center ellipse. Likewise, the green dashed lines indicate the boundaries of the vertical diameter of the ellipse. The LEDs located interior to these boundary lines are turned on. The arrows on each side of the mat indicate the direction of the lights turning on, which corresponds to inhalation. The auditory feedback is designed by using Processing Beads Library to match the visual feedback.

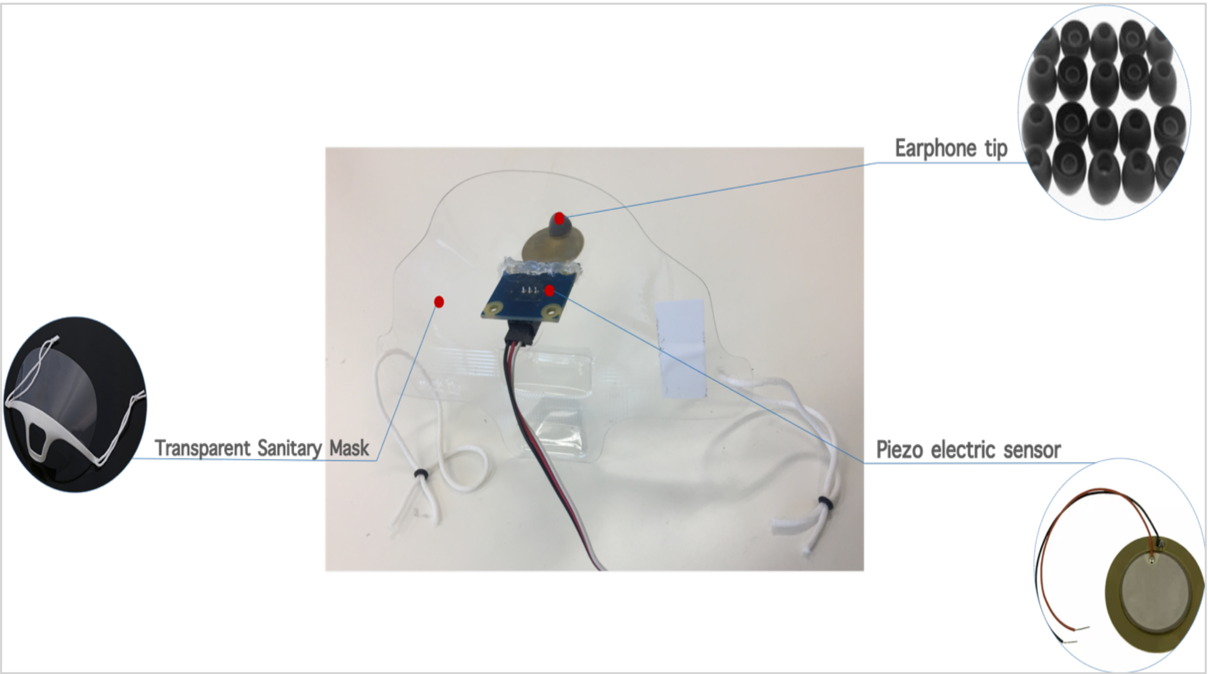


Figure 4. Initial prototype of breathing detector.

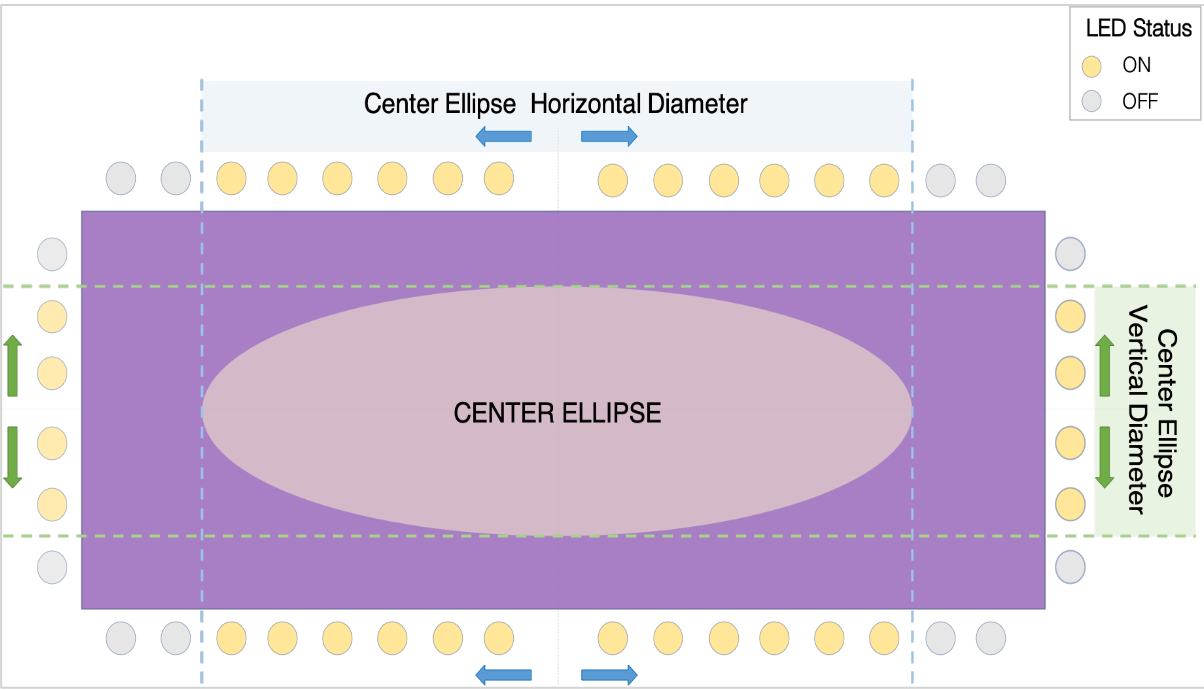


Figure 5. Description of visual feedback design using led strips adhered to the sides of yoga mat.

A Refined Design

After testing with the initial prototype, we realized detecting breathing phases with a piezo-electric sensor is notably unreliable. It was also difficult to account for the pauses in between inhalation and exhalation. Thus, we decided to use other breathing sensing mechanism based on prior works by using Inertial Measurement Unit (IMU) sensors. The details on the development of this respiration phase detector are described in the next chapter. A refined design of biofeedback-based yoga mat for breathing practices is shown in Figure 6.

Figure 6. A refined design of biofeedback-based mat for yoga breathing practices

IV Development of Respiration Phase Detector

4.1 Overview

To the best of our knowledge, there is no commercially available low-cost respiration sensor that reports respiration stages. Thereby, we develop a cost-effective respiration phase detector for at-home exercises using IMUs based on previous works.

The overarching challenge in respiration sensing is balancing the pros and cons to find the most appropriate method that fits into the study context. In this work, the main objective of sensing is to detect and identify respiration phases in typical yoga practice. For instance, the sensing mechanism should correctly distinguish inhalation from exhalation while the yoga practitioner is performing and maintaining various yoga poses. For this reason, the sensing mechanism should be robust to body postures as well as to the surrounding noise. In order to meet these two conditions, we built a respiration sensing chest belt using two IMU (Inertial Measurement Units) sensors. One IMU sensor is placed on top of a person's solar plexus as suggested in [46] and the other is placed on the back of the person in a position parallel to the one on solar plexus. The relative rotation and acceleration differences of two sensors from gyroscope and accelerometer are used for identifying the respiration phases.

A complete human breathing cycle consists of four basic stages: inspiration, expiration and rest [47]. In this study, we divide a breathing cycle into four phases which are inhalation, retention of inhalation, exhalation, and retention of exhalation. This four-stage cycle comes from a breathing practice (*pranayama*) known as *sama vritti* wherein inhalation (*puraka*), exhalation (*rechaka*), retention after inhalation (*antara kumbhaka*), and retention after exhalation (*bahya kumbhaka*) are equal in length [48]. Here, the development of a respiration phase detector for detecting the four respiration phases is presented in detail.

4.2 Respiration Phase Detector Prototype

The respiration phase detector prototype takes the form of a chest strap. Two VR IMU[3] sensors used detecting changes in the chest movements, specifically rotation and acceleration. These sensors wired to Arduino Fio are mounted inside 3D printed cases, which are attached to the strap as shown in Figure 7(a). The prototype is designed to be worn around the chest or diaphragm so that one sensor is

[3] https://learn.sparkfun.com/tutorials/qwiic-vr-imu-bno080-hookup-guide/all

placed on top of solar plexus and the other on the opposite side in parallel. The sensors are configured to obtain rotation in the *y*-axis, acceleration in the *x*-axis and to transmit these raw data wirelessly to Processing through Zigbee. The orientation of the sensor and its axis are shown in Figure 7(b). The rotational changes in y-axis reflect expansion and compression of diaphragm and acceleration in x-axis represents the orientation of the sensor. Relative acceleration and rotation are derived from two sets of raw rotation and acceleration values.

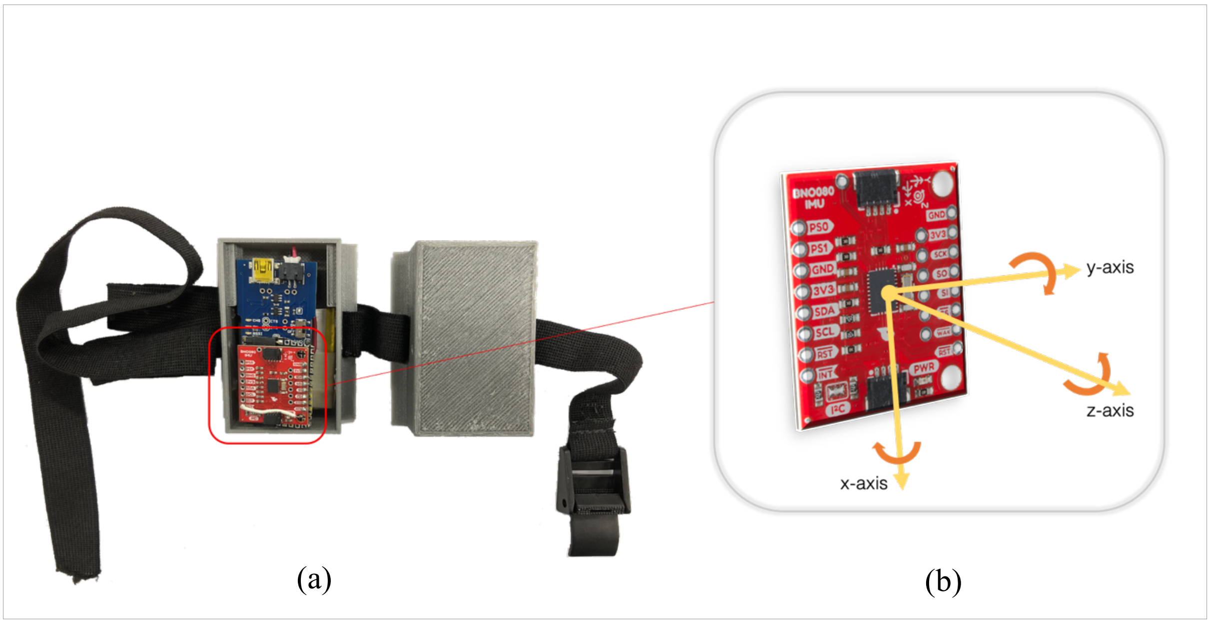


Figure 7. Hardware Prototype. (a) Prototype of respiration phase detector, (b) VR IMU orientation and three axes.

4.3 Data Collection Study

4.3.1 Aim

The main goal of this experiment is to collect sufficient breathing data in different pose variations. The breathing data is collected to train, build, and test classifiers for detecting breathing phases.

4.3.2 Participants

Five male and five female participants in age between 23 and 30 (Mean = 25.5, SD = 2.01) were recruited for data collection study. Five of the participants have practiced yoga regularly or irregularly prior to the experiment during the past few years. Four of these practitioners indicated having introduced to yogic breathing and two showed some confidence in diaphragmatic breathing. Three of the participants reported smoking about 10 cigarettes a day.

We specified that no prior yoga experience was required to participate. No restrictions were imposed in consideration of the potential end-users of the developed artifact. The suggested breathing training system is primarily designed for novice yoga practitioners who might not have been exposed to any type of breathing practices in the past. Each participant received 15,000 won as compensation for 90 minutes long study. This study has been approved by the university's Institutional Review Board (IRB).

4.3.3 Experimental Setup

The experimental setup is shown in Figure 8. We used a commercial respiration sensor (SA9311M) with FlexComp Infiniti[4] encoder to capture ground truth respiration signals. The encoder, attached to the back of participants, was configured to transmit high-resolution data to Biograph Infiniti software platform. All data obtained from the flex sensor were archived and managed in this software. Our prototype was worn thoracically over clothing along with the flex sensor. All data from our prototype was transferred to Processing IDE through Xbee wireless communication at a sample rate of 60 Hz. A beam projector screen was set up for displaying online yoga tutorials and a Bluetooth speaker was placed for delivering auditory cues for different phases of breathing.

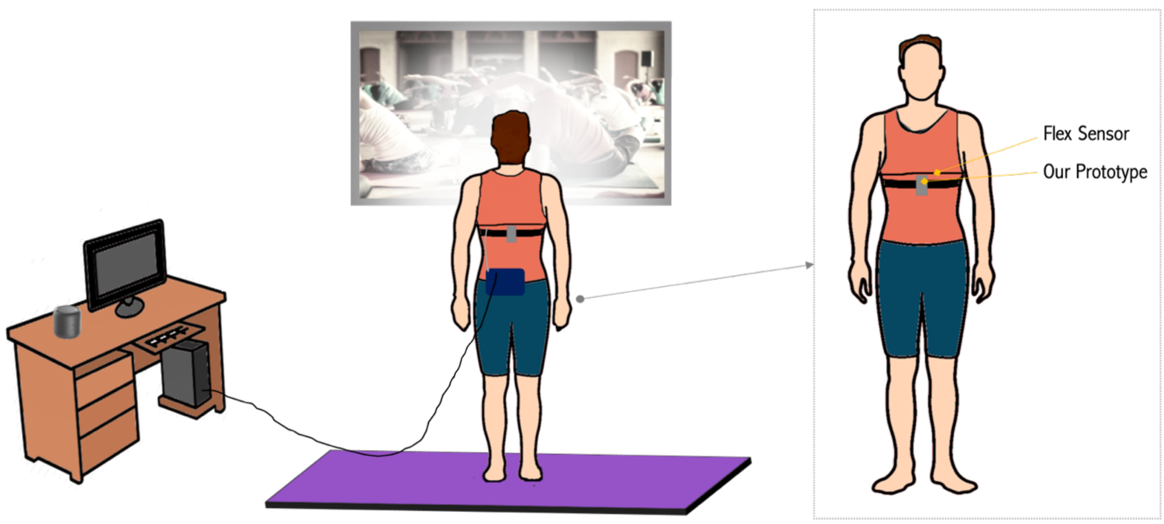


Figure 8. Experimental setup for data collection study. Flex sensor and our prototype are both worn around the chest of each participant, and the encoder of flex sensor on the waist. The poses are shown on the projector screen and the auditory cues are delivered through the Bluetooth speaker.

[4] http://thoughttechnology.com/index.php/flexcomp-system-with-biograph-infiniti-software-t7555m.html

4.3.4 Materials and Methods

The materials used in this experiment are an auditory guide for breathing and online video tutorials for poses. Auditory cues are designed to implicitly convey when to inhale, exhale, or hold breath. How we designed these cues is described in the subsection *Auditory Guide*. Publicly available tutorials from YouTube are used to drive participants through the sequence of movements to reach the desired pose.

Auditory Guide

The auditory guide consists of an increasing tone to indicate inhale, a decreasing tone to indicate exhale, and no tone to indicate retention. This guide is generated using beads library in Processing IDE. The tones generated from sine waves at a different frequency. The 440Hz tone is used for inhaling and 200Hz tone is used for exhaling. The duration of each tone is set equivalent to the duration of each phase, which is 3000 milliseconds. The amplitude of each tone is mapped to exponential function so that sound does not abruptly begin nor end.

Poses

To account for breathing in different body postures, we incorporated three yoga poses shown in Figure 9. The first pose is a sitting pose sometimes referred to as the easy pose (*Sukhasana*). This relaxing pose is used for capturing the baseline. The second pose is a bending pose, namely the downward-facing dog pose (*Adho Mukha Svanasana*). The last pose chosen for this experiment is the tree pose (*Vrksasana*), which is a type of standing pose. It is also a pose widely practiced for strengthening a sense of balance. All of these are recommended poses for beginner level practitioners. Thus, these poses are relatively easy to learn and follow with instructions from online video tutorials. However, variations and props were available for participants who did not feel steady with any of these poses.

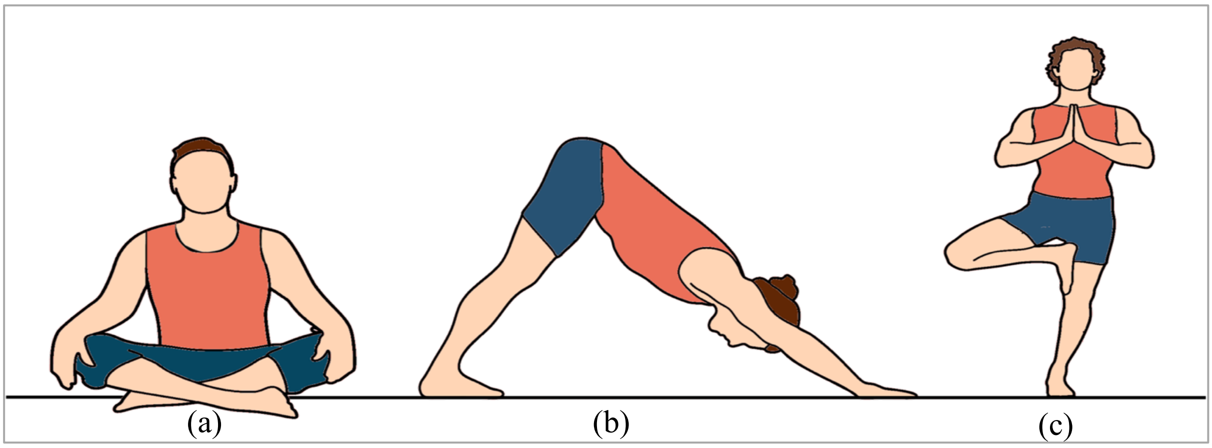


Figure 9. Yoga poses used in the experiment. (a) Easy, (b) Downward-Facing Dog, (c) Tree.

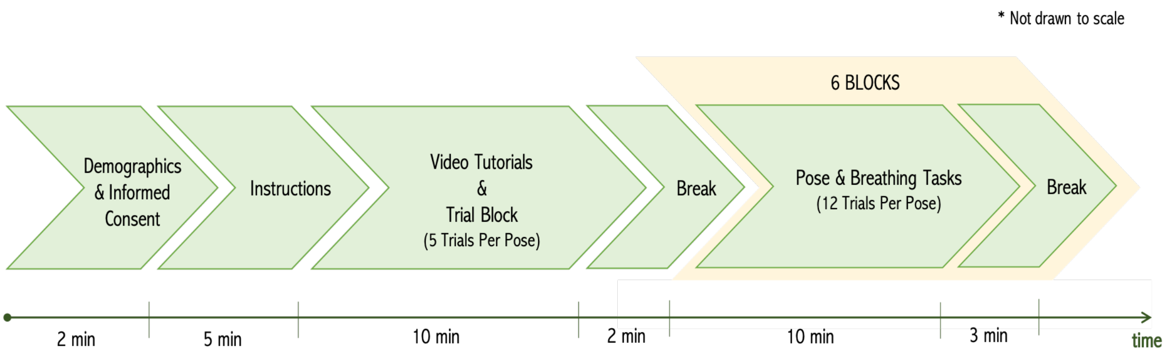


Figure 10. Overview of experimental procedure.

Procedure

The overview of the experimental procedure is shown in Figure 10. All participants were asked to fill out demographic information and signed an informed consent form prior to their participation. The collected information about participants includes age, gender, level of expertise in asanas and pranayama, other breathing techniques, and smoking status. Instructions about the experiment were given next. After participants read through written instructions, each wore two chest belts: our prototype and flex sensor for capturing the ground truth.

When sensor calibration was complete, participants watch video tutorials for diaphragmatic breathing and each of the poses. All participants, regardless of their experience with yoga, watched online tutorials. After watching the tutorial video for each pose, they were asked to stay in that posture and practice breathing following the auditory guide. Assuming their compliance, the data stream from IMU were labeled accordingly. That is, when the tone for inhalation is played, participant's data at that point of time is labeled "inhale". In the trial block, there were five trials for each pose. In other words, five complete breath cycles were logged for each pose. Participants were asked to have a rest for 2 minutes after completing their trial session.

After the trial block, a block consists of three poses with 12 trials for each of them. Again, this means participants were prompted with a task with 12 consecutive breathing cycles. The order in which the poses appear were counterbalanced. At the end of each block, 3 minute-break was given. There was a total of six blocks in the experiment.

4.4 Building Classifiers

Using the relative rotation and acceleration data captured from the study, we built and tested machine learning models for classifying respiration phases. The primary goal of building and testing these models is to examine whether or not building a generalized model that can recognize respiration phases for all users is feasible. The feasibility of this model is determined directly from classifier performance.

4.4.1 Data Preprocessing

In order to generate feature vectors for building classifiers, we preprocess data by removing outliers, applying smoothing filters, and normalizing.

Outlier Removal

There are three types of outliers in our data. First is misread data that is labeled as NaN, which stands for not a number. Another type of outlier is the empty ones. They occur when the stream data is shifted in time. For example, when two floating values are misread as one, all values in that string are shifted left leaving the last value empty. The last type of outliers also results from sensor misreading. It is when the sensor reading reports values out of range. For example, the sensor may show 980 as acceleration in x-axis due to an error while the possible range of acceleration in our study is from 0 to 9.8, which is the standard value of gravity.

Instead of removing all instances containing the outliers, we replace the outliers with an average of five previous values. We manipulate outliers this way because our data is in stream form. This process is done within the same pose in a block.

Smoothing

When all outliers were replaced, we applied a moving average filter to the data for smoothing. To preserve the original shape of the curve, we applied two separate smoothing filters in a sequence. For example, moving average filter with a window size of 50 was applied to the raw signal per pose in each block. Another moving average filter with a window size of 30 was applied to the smoothed signal. We refrain from applying a filter with a larger window to the raw signal because typical latency with moving average was observed. The raw data and the filtered data are shown in Figure 11.

In the plot, the values on y-axis indicate angular velocity; thus, greater the change, greater the distance is from the baseline which is around 0. The positive and negative ranges show the direction in which the sensor rotates. The axis labeled as “Time Order” is not the actual time. It only shows data samples in the order they are captured. The interval between adjacent samples is approximately 16 seconds long. We segment the signal into four stages of breathing according to the auditory cues displayed to participants. The signal with the corresponding respiration phase is shown in Figure 11.

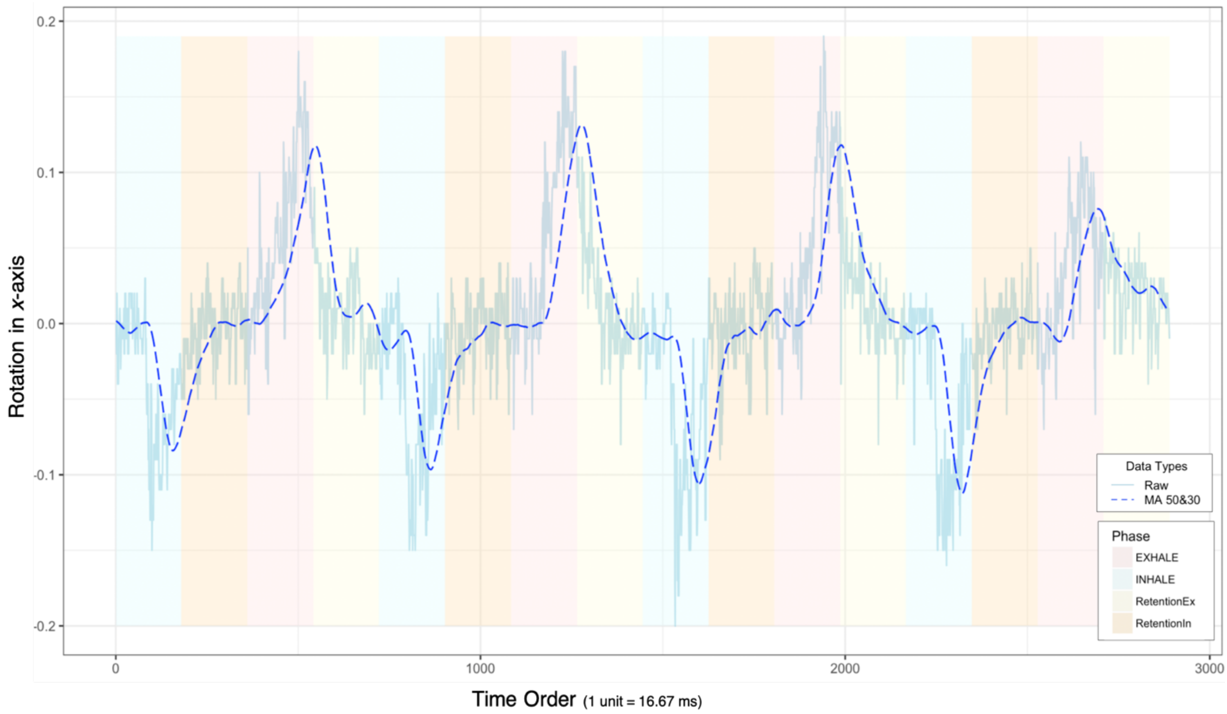


Figure 11. Plot of data samples and the corresponding phases in which they are captured. The angular velocity is indicated in y-axis. A single unit in x-axis indicates a sample in 16 second-intervals. The light blue line is raw data stream and the dashed blue line is stream of data after smoothing with moving average filter.

Normalization

The final step in preprocessing is normalization which scales the data into certain range. We normalized our data using following formula:

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

Data are normalized by each pose in each block following previous mentioned approaches in data manipulation.

4.4.2 Feature Vectors

Feature vectors were generated from normalized datasets. We derived a list of features based on previous work on activity recognition from the acceleration signal [49]. The features are descriptive statistics such as min, max, median, mean, range, standard deviation, RMS, crest factor, kurtosis, and skewness. Additional features computed are the angle of change, indices difference, and pearson2coefficients. The angle of change is the angle in radian between min and max. Indices difference is the difference between the max index and min index. Hence, there are 14 features for each set of sensor readings from the anterior and posterior part of the body, and the difference between the two.

A sliding window of 85 samples with 90% overlap is used to generate an instance of feature vectors. Feature vectors are generated only when the sliding window completely lies within a respiration phase, which we label as the dominant phase.

4.4.3. Comparison with the Ground Truth

Before proceeding to build classifiers, we removed instances from the dataset if they come from noisy trials. The trials that are spotted as noisy are the ones in which we cannot identify whether or not the participants did comply with the auditory guide. For instance, a trial containing patterns of a complete respiration cycle is considered noisy if the clear inhalation, retention, and exhalation patterns are not observed. These trials with noisy patterns are excluded from the feature vector dataset. For example, all trials except 0, 4, and 5 in Figure 12 are excluded from the dataset. This is manually checked by the experimenter by examining the breathing patterns in Biograph software.

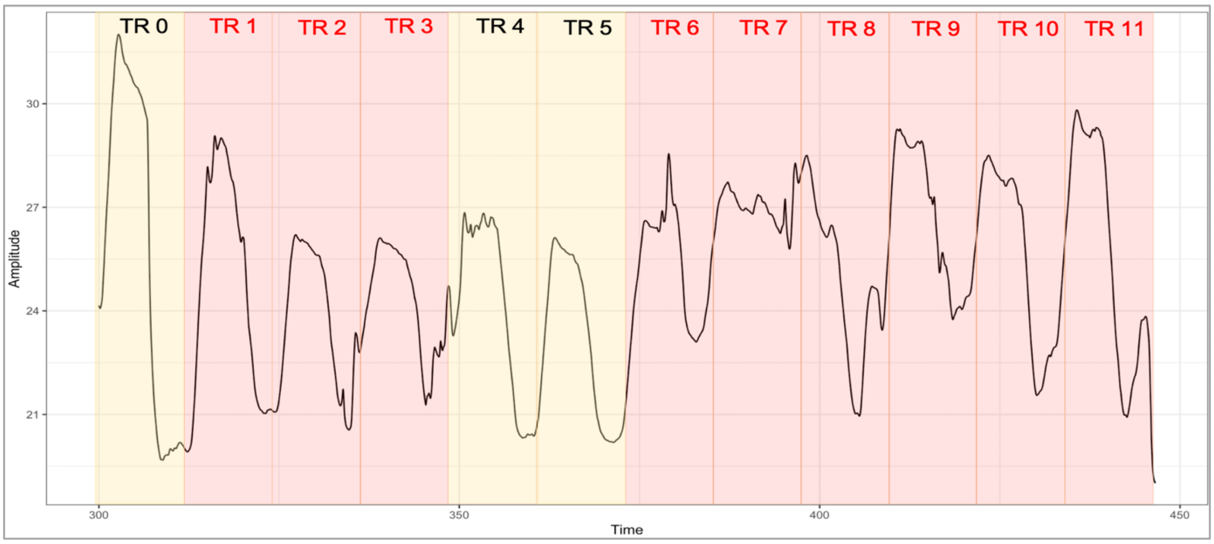


Figure 12. Plot of breathing patterns observed from commercial respiration sensor. Each colored pane indicates a single breath cycle. Trials in red colors are removed from dataset as they contain noise.

4.4.4 Classifiers and Feature Selection

Respiration Phases

We built per-user classifiers with Support Vector Machine (SVM) using a second order polynomial kernel with Scikit-learn package in Python. Optimal performance was attained with the complexity parameter set to 0.01. For training the model, we used a percentage split of 75% leaving the other 25% of the data as the test dataset. We also set an option to preserve the order for percentage split. We set this option because the instances do not represent a single independent event. In the dataset, there are 32 instances from a complete breath, 8 instances from each phase. The idea is to classify phases of breath with a classifier built from other breaths of a single person. Shuffling the instances would violate this idea since some instances of a single breath may be used to train the model while the rest be used for testing.

The important attributes for classifying respiration phases are determined based on information gain evaluation. The worth of a feature is evaluated by calculating the information gain or the entropy with respect to the output class [50]. The entropy ranges from 0 to 1 where 0 indicates no information. Top nine attributes that overlap in top 15 attributes selected for each per-user classifiers are listed in Table 2. The sensor type in the leftmost column denotes the sensor associated with the attribute. For example, the first row means Gyro readings (angular velocity) from sensor A (placed on the thorax), sensor B (placed on back), and the difference of these two are all meaningful features. The top 15 attributes for each per-user classifiers are plotted in Figure 13. For many of the subjects, attributes generated from sensor A (on the thorax) and the difference between two sensors are selected as important features.

Table 2. Important features for classifying respiration phases.

Sensor Type	Attribute Name
All (A, B, A-B)	Gyro Max
All (A, B, A-B)	Gyro Min
All (A, B, A-B)	Gyro Mean
All (A, B, A-B)	Gyro Angle of Change
All (A, B, A-B)	Gyro Min/Max Indices Difference
All (A, B, A-B)	Gyro RMS
All (A, B, A-B)	Gyro Median
B, A-B	Accel Min
B, A-B	Accel Max

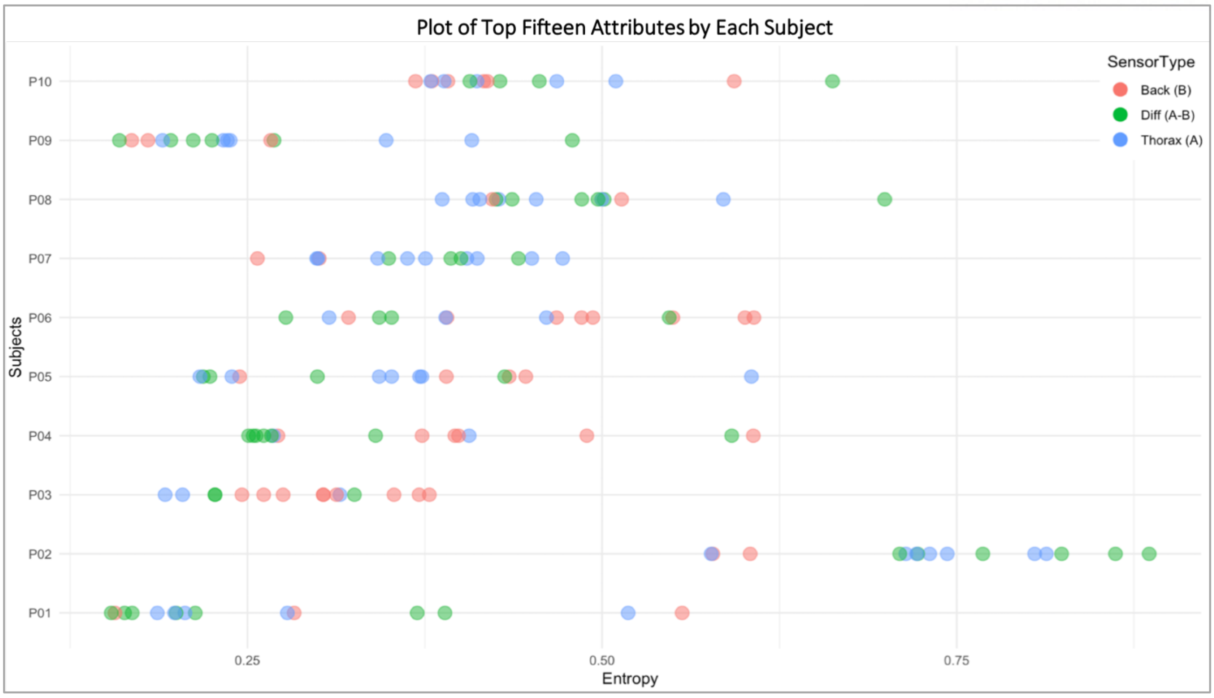


Figure 13. Plot of top fifteen attributes for per-user classifiers by each subject. The entropy is the information gain with respect to output class, and it ranges from 0 to 1 where 0 indicates no information.

Poses

The same dataset was used to build a model for classifying the pose types: easy (sitting), tree (standing), and downward-facing dog (bending). The type of classifier, parameters, and the process for building the classification model are all kept exactly same.

4.4.5 Classifier Performance

Two per-user classifiers are built from each user's dataset: one classifies phases in a breath and the other classifies the three poses.

Respiration Phases

Building a single classifier that can be generally used among all users is ideal. However, the mean performance scores of per-user classifiers are summarized in Table 3 show generalized classifier cannot be modeled. The classification accuracy for all poses on average is approximately 70%. When per-user classifiers were built per pose, the classification rates for easy pose significantly increased but the rates decreased for the other two poses. This may imply that our prototype is able to detect chest movements well in sitting pose, which is a relaxed state. In contrast, this may suggest that the range of participants' chest movements are negligible in a certain pose based on their ability and experience. Ten participants' individual scores based on the pose types are scaled for comparison as shown in Figure 14. The y-axis represents subject numbers from 1 to 10. A lower number in the scale symbolizes a low score. Therefore, the points located on the far-right side indicate high classification scores. For example, points of subject 2 aggregated on the far-right side mean classification scores are high for subject 2 regardless of the pose type. Contrarily, subject 8's scores are spread along the scale. The classification rates for this participant is extremely low in tree pose but very high for easy and downward-facing dog pose. From these variations on scores depending on the pose and user, it is difficult to draw a pattern on what exactly may have affected these scores.

Table 3. Mean performance scores of per-user classifiers for respiration phase detection.

μ(σ)

Pose Type	TP Rate	FP Rate	Precision	Recall	F-Measure
All	0.6930 (0.1218)	0.1023 (0.0406)	0.7044 (0.1186)	0.6930 (0.1218)	0.6913 (0.1240)
Easy	0.7912 (0.1667)	0.0690 (0.0545)	0.8135 (0.1388)	0.7910 (0.1666)	0.7843 (0.1776)
Down-Dog	0.6192 (0.2114)	0.1275 (0.0713)	0.6351 (0.2062)	0.6192 (0.2114)	0.6137 (0.2170)
Tree	0.6806 (0.1781)	0.1049 (0.0575)	0.7213 (0.1722)	0.6799 (0.1788)	0.6512 (0.2131)

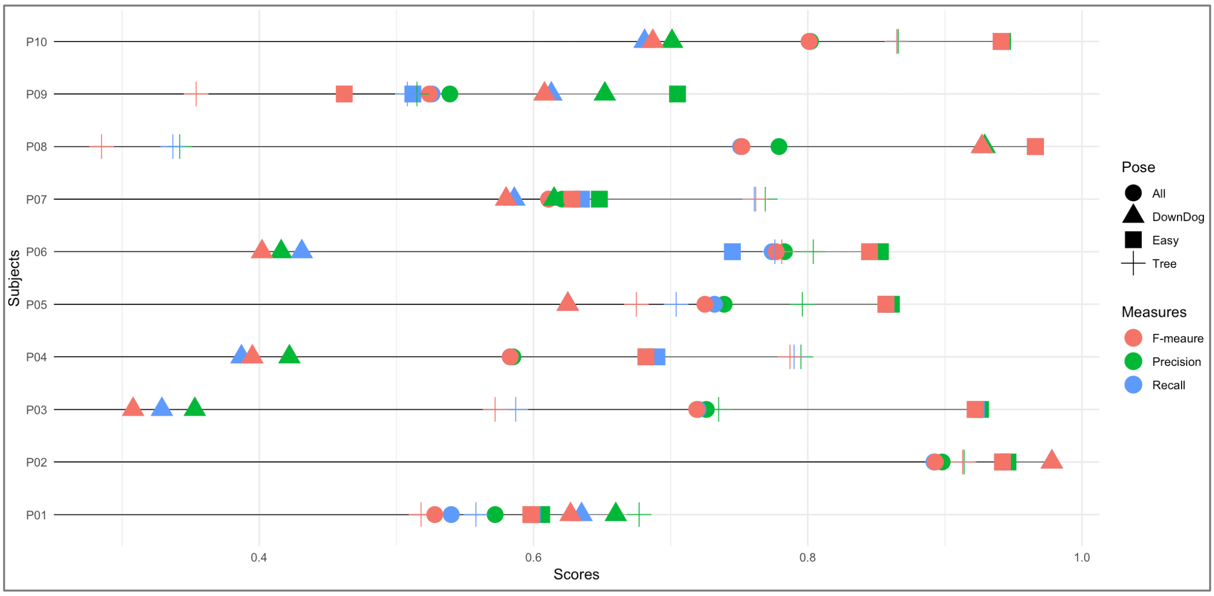


Figure 14. Plot of performance scores for poses by each subject. The scores (x-axis) are classification measures: F-measure, Precision, and Recall color coded as pink, green, and blue respectively. The poses are mapped to different shapes. A higher score implies the pose was well-classified.

In addition, mean performance scores from classifiers using a single sensor and multiple sensors are compared in Table 4. The classifiers built with data from multiple sensors perform better than using measurements from a single motion sensor placed on top of solar plexus where the motion changes mainly occur.

Table 4. Comparison of mean performance scores of a single sensor and multiple sensors.

$\mu(\sigma)$

Sensor Type	TP Rate	FP Rate	Precision	Recall	F-Measure
All (A + B)	0.6930 (0.1218)	0.1023 (0.0406)	0.7044 (0.1186)	0.6930 (0.1218)	0.6913 (0.1240)
Thorax (A)	0.5013 (0.1683)	0.1661 (0.0559)	0.5100 (0.1679)	0.5013 (0.1683)	0.4901 (0.1579)

Poses

The mean performance scores of per-user classifiers for detecting three poses are summarized in Table 5. The mean classification accuracy from per-user classifiers show that our prototype is able to correctly detect three poses for each user.

Table 5. Mean performance scores of per-user classifiers for pose detection.

$\mu(\sigma)$

TP Rate	FP Rate	Precision	Recall	F-Measure
0.9777(0.0458)	0.1096 (0.3135)	0.9779(0.0458)	0.9777(0.0458)	0.9775(0.0464)

V Discussion and Conclusion

5.1 Discussion

5.1.1 Respiration Phase Detection

For respiration phase detection, we built per-user classifiers per pose due to the variation of classification rates among users and the poses. As previously mentioned, this may have resulted from individuals' ability to perform and sustain different yoga poses. We assume the problem is not about one's ability to breathe nor about the failure of our prototype design to detect movements from respiratory motion. Our assumption is based on the fact that reported scores from the majority of per-user classifiers for the easy pose are relatively high. This means the changes in acceleration and rotation from breathing well-reflected the respiration phases in the particular pose. Therefore, it would be misleading to contemplate the prototype design was not suitable for phase detection.

However, the low performance on classifiers for a difficult pose like the downward-facing dog may suggest that our prototype may not be very useful in poses that put the upper body under pressure. In fact, the accuracy from the classifier for downward-facing dog pose was lowest among all poses for more than half of the participants. This is presumably because the range of expansion and contraction of an individual is dependent on the body posture. Thus, the range of participants' angular changes, the best attribute selected, may become negligible for detection in a certain pose based on an individual's ability and experience.

Nonetheless, the classifier is designed to make instantaneous judgments so the classification accuracy of .70 does not mean the classifier misclassifies every 3 out of 10 breaths. The accuracy rather implies that in a single respiration phase, 3 out of 10 instances are incorrectly classified. Thus, there is a greater chance for classifying a respiration phase correctly if we group several consecutive instances and inspect them in a sequence. We also note that for generating the dataset, only the data from a specific frame are extracted. In practice, the instances will be generated every 160 milliseconds. That is, if a person's duration of a respiration phase is 4 seconds, approximately 25 judgments will be made. Therefore, we believe the classification of breathing phases in practice more reliable in practice.

5.1.2 Pose Detection

Aside from respiration phase detection, our prototype is able to accurately distinguish three yoga poses. Considering the types of yoga poses, this can be a promising result for designing applications to adopt into yoga practices. As an example, an application that logs a practitioner's practice activity can possibly be suggested. The application can provide a summary report of practiced pose types so that practitioners can maintain a balance of poses in their routine. This classifier can also be applied to other fields. For instance, this can support groups of people in need of help with posture changes every few hours.

5.2 Limitations and Future Work

A major limitation of this study is building reliable classifiers for respiration phase detection due to the lack of a standard dataset for human breathing that is correctly labeled by respiration phases. Without such dataset, it is difficult to collect a clean breathing data especially when the subject is making specific body postures. Moreover, there is no experimental equipment supplying a ground truth to refer to. Thus, the process of comparing the breathing pattern and confirming subjects' compliance was carried out manually by the experimenter. This manual process is prone to human error.

Another limitation of this study is using the machine learning classification for detecting breathing phases. This method has not been used considerably in HCI context previously. For this reason, adopting machine learning classification methods can be interesting and novel for respiration detection studies. However, the results from our study show that classification rates do not exceed previously suggested approaches. Perhaps, machine learning based classification may not be a suitable method for our approach in making instantaneous judgments for respiration phase detection. Therefore, more studies are needed on machine learning classification methods for respiration detection and methods for respiration phase detection.

Acknowledging this limitation, we pose two directions for our future work. Both directions will be on the application and evaluation of the developed artifact. The first approach is a typical comparative study to investigate which feedback modality effective and preferred. The evaluation metrics will be both quantitative and qualitative. Quantitative analyses will be possible based on the ratio of respiration phases can be derived from the estimated duration of each respiration phase in a breathing cycle. Qualitative analyses of the system can also be produced by surveying participants with a questionnaire after the use. Based on the results of the data collection study, building per-user classifiers for this basic evaluation study is a burden. Therefore, a wizard-of-oz approach for replacing a breathing phase detector would be more appropriate.

Another approach in consideration is in-the-wild study with a few novice yoga practitioners. There are several requirements that need to be met in order to conduct this study. Most importantly, a deployable system should be established so that practitioners can readily use it. In other words, the system must have an interface designed to guide users on creating their own respiration phase classifier. Prior to this, we need to make sure building and saving machine learning models on the mobile application are viable. If it is feasible to train and use the classifier, we need to test and finalize the number of breaths required for building classifier with a reasonable performance. When all these requirements are met, we can conduct a usability study to explore how the system including the feedback is received by our end-users.

5.3 Conclusions

One of the exercises that can be done alone at home without fancy equipment is yoga. It is not only an exercise that involves physical movements, but also a representative practice for meditative purposes to concentrate on oneself. Although yoga is a practice for an individual to unite their own mind and body, it is difficult to begin this practice alone as a novice due to lack of experiences and skills.

For instance, a common way to learn and practice yoga at home is to watch video tutorials online. However, these tutorials are not capable of giving useful feedback to the inexperienced yogis. Among various aspects of yoga, breathing techniques are addressed to be challenging to beginners because it is difficult to learn these skills from just watching a demonstration.

To this end, our context-driven approach to propose a system design that can potentially replace expert instructions and guidance for breathing training in a yoga practice is notable. This standalone system may also be used for other breath regulation practices for alleviating stress and anxiety [51] coping with negative emotional states [52, 53], and in turn, provoking a calm and relaxed state of mind [27]. In addition, the respiration phase detector can be applied to other exercises as maintaining a stable breathing pace is important in other physical exercises like running.

In our exploratory work on breathing phase detection using machine learning, we strive to understand the manipulation of human data collected in a variety of contexts. The study results shed lights on an innate difficulty in collecting correctly labeled breathing data under movement-involved circumstances. This work also pinpoints machine learning classification approaches may not always be the best methods to incorporate in HCI studies depending on the characteristics of the data, context, and study design.

REFERENCES

[1] S. Moran, N. Jäger, H. Schnädelbach, and K. Glover, "Exopranayama: a biofeedback-driven actuated environment for supporting yoga breathing practices," Personal and Ubiquitous Computing, vol. 20, no. 2, pp. 261–275, 2016.

[2] S. B. Khalsa, "Yoga as a therapeutic intervention," Principles and practice of stress management, vol. 3, pp. 449–462, 2007.

[3] G. S. Birdee, A. T. Legedza, R. B. Saper, S. M. Bertisch, D. M. Eisenberg, and R. S. Phillips, "Characteristics of yoga users: results of a national survey," Journal of General Internal Medicine, vol. 23, no. 10, pp. 1653–1658, 2008.

[4] T. Field, "Yoga research review," Complementary therapies in clinical practice, vol. 24, pp. 145–161, 2016.

[5] S. Feiereisen, "9 simple ways to add exercise into your work and home routines," May 2019. [Online]. Available: https://www.businessinsider.com/ exercise-tips-work-home-routine-2019-5

[6] A. Singh, A. Klapper, J. Jia, A. Fidalgo, A. Tajadura-Jiménez, N. Kanakam, N. BianchiBerthouze, and A. Williams, "Motivating people with chronic pain to do physical activity: opportunities for technology design," in Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. ACM, 2014, pp. 2803–2812.

[7] H. Schäfer, J. Bachner, S. Pretscher, G. Groh, and Y. Demetriou, "Study on motivating physical activity in children with personalized gamified feedback," in Adjunct Publication of the 26th Conference on User Modeling, Adaptation and Personalization. ACM, 2018, pp. 221–226.

[8] M. T. Baranowski, P. K. Bower, P. Krebs, C. J. Lamoth, and E. J. Lyons, "Effective feedback procedures in games for health," Games For Health: Research, Development, and Clinical Applications, vol. 2, no. 6, pp. 320–326, 2013.

[9] K. Rector, C. L. Bennett, and J. A. Kientz, "Eyes-free yoga: An exergame using depth cameras for blind & low vision exercise," in Proceedings of the 15th International ACM SIGACCESS Conference on Computers and Accessibility, ser. 33 ASSETS '13. New York,

NY, USA: ACM, 2013, pp. 12:1–12:8. [Online]. Available: http://doi.acm.org/10.1145/2513383.2513392

[10] K. Maybach, A. Nagargoje, and T. Sokoler, “Social yoga mats: Reinforcing synergy between physical and social activity,” in CHI ’11 Extended Abstracts on Human Factors in Computing Systems, ser. CHI EA ’11. New York, NY, USA: ACM, 2011, pp. 1561–1566. [Online]. Available: http://doi.acm.org/10.1145/1979742.1979808

[11] D. S. Elvitigala, D. J. Matthies, L. David, C. Weerasinghe, and S. Nanayakkara, “Gymsoles: Improving squats and dead-lifts by visualizing the user’s center of pressure,” in Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, ser. CHI ’19. New York, NY, USA: ACM, 2019, pp. 174:1–174:12. [Online]. Available: http://doi.acm.org/10.1145/3290605.3300404

[12] R. Tang, X.-D. Yang, S. Bateman, J. Jorge, and A. Tang, “Physio@ home: Exploring visual guidance and feedback techniques for physiotherapy exercises,” in Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems. ACM, 2015, pp. 4123–4132.

[13] M. Prpa, K. Tatar, J. Françoise, B. Riecke, T. Schiphorst, and P. Pasquier, “Attending to breath: Exploring how the cues in a virtual environment guide the attention to breath and shape the quality of experience to support mindfulness,” in Proceedings of the 2018 Designing Interactive Systems Conference, ser. DIS ’18. New York, NY, USA: ACM, 2018, pp. 71–84. [Online]. Available: http://doi.acm.org/10.1145/3196709.3196765

[14] B. Yu, L. Feijs, M. Funk, and J. Hu, “Breathe with touch: a tactile interface for breathing assistance system,” in Human-Computer Interaction. Springer, 2015, pp. 45–52.

[15] I. Aslan, H. Burkhardt, J. Kraus, and E. André, “Hold my heart and breathe with me: Tangible somaesthetic designs,” in Proceedings of the 9th Nordic Conference on Human-Computer Interaction, ser. NordiCHI ’16. New York, NY, USA: ACM, 2016, pp. 92:1–92:6. [Online]. Available: http://doi.acm.org/10.1145/2971485.2996727

[16] H. Schnädelbach, A. Irune, D. Kirk, K. Glover, and P. Brundell, “Exobuilding: Physiologically driven adaptive architecture,” ACM Trans. Comput.-Hum. Interact., vol. 19, no. 4, pp. 25:1–25:22, Dec. 2012. [Online]. Available: http://doi.acm.org/10.1145/2395131.2395132

[17] H. Sjöman, N. Soares, M. Suijkerbuijk, J. Blindheim, M. Steinert, and D. T. Wisland, "The breathing room: Breathing interval and heart rate capturing through ultra low power radar," in Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems, ser. CHI EA '18. New York, NY, USA: ACM, 2018, pp. D207:1–D207:4. [Online]. Available: http://doi.acm.org/10.1145/3170427.3186473 34

[18] N. Moraveji, B. Olson, T. Nguyen, M. Saadat, Y. Khalighi, R. Pea, and J. Heer, "Peripheral paced respiration: Influencing user physiology during information work," in Proceedings of the 24th Annual ACM Symposium on User Interface Software and Technology, ser. UIST '11. New York, NY, USA: ACM, 2011, pp. 423–428. [Online]. Available: http://doi.acm.org/10.1145/2047196.2047250

[19] P. E. Paredes, Y. Zhou, N. A.-H. Hamdan, S. Balters, E. Murnane, W. Ju, and J. A. Landay, "Just breathe: In-car interventions for guided slow breathing," Proc. ACM Interact. Mob. Wearable Ubiquitous Technol., vol. 2, no. 1, pp. 28:1–28:23, Mar. 2018. [Online]. Available: http://doi.acm.org/10.1145/3191760

[20] M. Stafford, F. Lin, and W. Xu, "Flappy breath: A smartphone-based breath exergame," in 2016 IEEE First International Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE). IEEE, 2016, pp. 332–333.

[21] T. Sonne and M. M. Jensen, "Chillfish: A respiration game for children with adhd," in Proceedings of the TEI '16: Tenth International Conference on Tangible, Embedded, and Embodied Interaction, ser. TEI '16. New York, NY, USA: ACM, 2016, pp. 271–278. [Online]. Available: http://doi.acm.org/10.1145/2839462.2839480

[22] J. Marshall, D. Rowland, S. Rennick Egglestone, S. Benford, B. Walker, and D. McAuley, "Breath control of amusement rides," in Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, ser. CHI '11. New York, NY, USA: ACM, 2011, pp. 73–82. [Online]. Available: http://doi.acm.org/10.1145/1978942.1978955

[23] M. Sra, X. Xu, and P. Maes, "Breathvr: Leveraging breathing as a directly controlled interface for virtual reality games," in Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems, ser. CHI '18. New York, NY, USA: ACM, 2018, pp. 340:1–340:12. [Online]. Available: http://doi.acm.org/10.1145/3173574.3173914

[24] J. Frey, M. Grabli, R. Slyper, and J. R. Cauchard, “Breeze: Sharing biofeedback through wearable technologies,” in Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems, ser. CHI ’18. New York, NY, USA: ACM, 2018, pp. 645:1–645:12. [Online]. Available: http://doi.acm.org/10.1145/3173574.3174219

[25] R.-H. Liang, B. Yu, M. Xue, J. Hu, and L. M. G. Feijs, “Biofidget: Biofeedback for respiration training using an augmented fidget spinner,” in Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems, ser. CHI ’18. New York, NY, USA: ACM, 2018, pp. 613:1–613:12. [Online]. Available: http://doi.acm.org/10.1145/3173574.3174187

[26] C. Huang, H. Chen, L. Yang, and Q. Zhang, “Breathlive: Liveness detection for heart sound authentication with deep breathing,” Proc. ACM Interact. Mob. Wearable 35 Ubiquitous Technol., vol. 2, no. 1, pp. 12:1–12:25, Mar. 2018. [Online]. Available: http://doi.acm.org/10.1145/3191744

[27] T. Sonne, T. Merritt, P. Marshall, J. J. Lomholt, J. Müller, and K. Grønbæk, “Calming children when drawing blood using breath-based biofeedback,” in Proceedings of the 2017 Conference on Designing Interactive Systems, ser. DIS ’17. New York, NY, USA: ACM, 2017, pp. 725–737. [Online]. Available: http://doi.acm.org/10.1145/3064663.3064742

[28] P. Tennent, D. Rowland, J. Marshall, S. R. Egglestone, A. Harrison, Z. Jaime, B. Walker, and S. Benford, “Breathalising games: Understanding the potential of breath control in game interfaces,” in Proceedings of the 8th International Conference on Advances in Computer Entertainment Technology, ser. ACE ’11. New York, NY, USA: ACM, 2011, pp. 58:1–58:8. [Online]. Available: http://doi.acm.org/10.1145/2071423.2071496

[29] H. Gollee and W. Chen, “Real-time detection of respiratory activity using an inertial measurement unit,” in Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE. IEEE, 2007, pp. 2230–2233.

[30] A. Gaidhani, K. S. Moon, Y. Ozturk, S. Q. Lee, and W. Youm, “Extraction and analysis of respiratory motion using wearable inertial sensor system during trunk motion,” Sensors, vol. 17, no. 12, p. 2932, 2017.

[31] F. Q. AL-Khalidi, R. Saatchi, D. Burke, H. Elphick, and S. Tan, “Respiration rate monitoring methods: A review,” Pediatric pulmonology, vol. 46, no. 6, pp. 523–529, 2011.

[32] O. B. Lubecke, P.-W. Ong, and V. Lubecke, “10 ghz doppler radar sensing of respiration and heart movement,” in Bioengineering Conference, 2002. Proceedings of the IEEE 28th Annual Northeast. IEEE, 2002, pp. 55–56.

[33] F. Q. Al-Khalidi, R. Saatchi, D. Burke, and H. Elphick, “Facial tracking method for noncontact respiration rate monitoring,” in Communication Systems Networks and Digital Signal Processing (CSNDSP), 2010 7th International Symposium on. IEEE, 2010, pp. 751–754.

[34] A. H. Alkali, R. Saatchi, H. Elphick, and D. Burke, “Thermal image processing for real-time non-contact respiration rate monitoring,” IET Circuits, Devices & Systems, vol. 11, no. 2, pp. 142–148, 2017.

[35] L. Rebenitsch, C. B. Owen, R. Ferrydiansyah, C. Bohil, and F. Biocca, “An exploration of real-time environmental interventions for care of dementia patients in assistive living,” in Proceedings of the 3rd International Conference on PErvasive Technologies Related to Assistive Environments, ser. PETRA ’10. New York, NY, USA: ACM, 2010, pp. 34:1–34:8. [Online]. Available: http://doi.acm.org/10.1145/1839294.1839335 36

[36] R. Sigrist, G. Rauter, R. Riener, and P. Wolf, “Augmented visual, auditory, haptic, and multimodal feedback in motor learning: a review,” Psychonomic bulletin & review, vol. 20, no. 1, pp. 21–53, 2013.

[37] M. Papastergiou, “Exploring the potential of computer and video games for health and physical education: A literature review,” Computers & Education, vol. 53, no. 3, pp. 603–622, 2009.

[38] N. Moraveji, B. Olson, T. Nguyen, M. Saadat, Y. Khalighi, R. Pea, and J. Heer, “Peripheral paced respiration: influencing user physiology during information work,” in Proceedings of the 24th annual ACM symposium on User interface software and technology. ACM, 2011, pp. 423–428.

[39] B. Yu, Y. Song, and L. Feijs, “Light bird: An animated biofeedback interface for coherent breathing,” Design and semantics of form and movement, p. 356, 2015.

[40] K. Wongsuphasawat, A. Gamburg, and N. Moraveji, “You can’t force calm: designing and evaluating respiratory regulating interfaces for calming technology,” in Adjunct

proceedings of the 25th annual ACM symposium on User interface software and technology. ACM, 2012, pp. 69–70.

[41] J. Harris, S. Vance, O. Fernandes, A. Parnandi, and R. Gutierrez-Osuna, “Sonic respiration: controlling respiration rate through auditory biofeedback,” in CHI’14 Extended Abstracts on Human Factors in Computing Systems. ACM, 2014, pp. 2383–2388.

[42] A. Ghandeharioun and R. Picard, “Brightbeat: Effortlessly influencing breathing for cultivating calmness and focus,” in Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems, ser. CHI EA ’17. New York, NY, USA: ACM, 2017, pp. 1624–1631. [Online]. Available: http://doi.acm.org/10.1145/3027063.3053164

[43] S. Davidoff, M. K. Lee, A. K. Dey, and J. Zimmerman, “Rapidly exploring application design through speed dating,” in International Conference on Ubiquitous Computing. Springer, 2007, pp. 429–446.

[44] S. H. Khandkar, “Open coding,” University of Calgary, vol. 23, p. 2009, 2009.

[45] R. Clarke, “The digital persona and its application to data surveillance,” The information society, vol. 10, no. 2, pp. 77–92, 1994.

[46] J. E. Hernandez and E. Cretu, “Respiratory effort monitoring system for sleep apnea screening for both supine and lateral recumbent positions,” in 2017 8th IEEE Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON). IEEE, 2017, pp. 191–197. 37

[47] “Breathing cycle.” [Online]. Available: http://www.pathwaymedicine.org/breathing-cycle

[48] “How to do sama vritti pranayama,” Sep 2017. [Online]. Available: http://breatheyogaandwellness.com/how-to-do-sama-vritti-pranayama/

[49] S. Kozina, M. Lustrek, and M. Gams, “Dynamic signal segmentation for activity recognition,” in Proceedings of International Joint Conference on Artificial Intelligence, Barcelona, Spain, vol. 1622, 2011, p. 1522.

[50] J. Brownlee, “How to perform feature selection with machine learning data in weka,” Jun 2019. [Online]. Available: https://machinelearningmastery.com/ perform-feature-selection-machine-learning-data-weka/

[51] G. Paul, B. Elam, and S. J. Verhulst, “A longitudinal study of students’ perceptions of using deep breathing meditation to reduce testing stresses,” Teaching and learning in medicine, vol. 19, no. 3, pp. 287–292, 2007.

[52] F. J. McClernon, E. C. Westman, and J. E. Rose, “The effects of controlled deep breathing on smoking withdrawal symptoms in dependent smokers,” Addictive Behaviors, vol. 29, no. 4, pp. 765–772, 2004.

[53] R. Jerath, M. W. Crawford, V. A. Barnes, and K. Harden, “Self-regulation of breathing as a primary treatment for anxiety,” Applied psychophysiology and biofeedback, vol. 40, no. 2, pp. 107–115, 2015.

Acknowledgements

During the last two years at UNIST, I have had wonderful opportunities to meet so many people and be mentored by some of the greatest minds. I would never be where I am today if I had never met the people I have met and the experiences I have had.

First of all, I would like to express my deepest sense of gratitude to Professor Ian Oakley for his invaluable guidance and supervision. He has always been patient with the progress I made and consistently steered me in the right direction at every stage of this work.

I also would like to express a sincere appreciation to Professor Hwajung Hong of the Department of Communication at Seoul National University for her painstaking kindness, timely advise, and extraordinary cooperation throughout the qualitative studies in this work.

Next, I would like to acknowledge Professor Gwanseob Shin and Professor Young-woo Park as the thesis committee members. I am gratefully indebted to them for their interests and useful comments on this thesis.

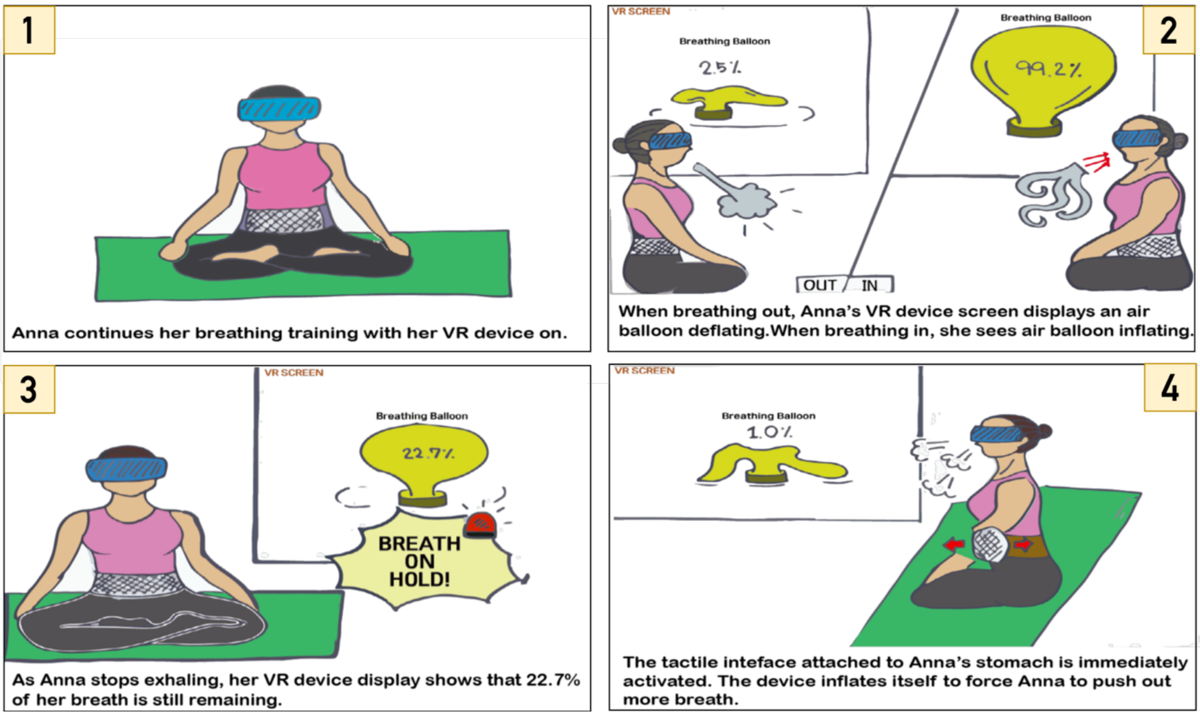
I would like to thank my fellow lab members: Mintra, Doyoung, Youngeun, Hyunjae, Hongmin, Youryang, Rasel, Yonghwan, and Eunyong for their continuous encouragement. I am extremely thankful to my second boss Mintra, who has been such a good colleague and a mentor. Her passion and an enthusiastic attitude on research have greatly motivated me on my research. I am also grateful to Youngeun for her genuine spirit for our weekly karaoke nights, Doyoung for sharing his knowledge and skills on microcontrollers and sensors, and Eunyong for his dad-jokes.

Finally, I would like to express my very profound gratitude to my parents, Sunny, Wonkyo, and Minsu for providing me with unfailing support throughout my years of study. This accomplishment would have not been possible without their support and encouragement.

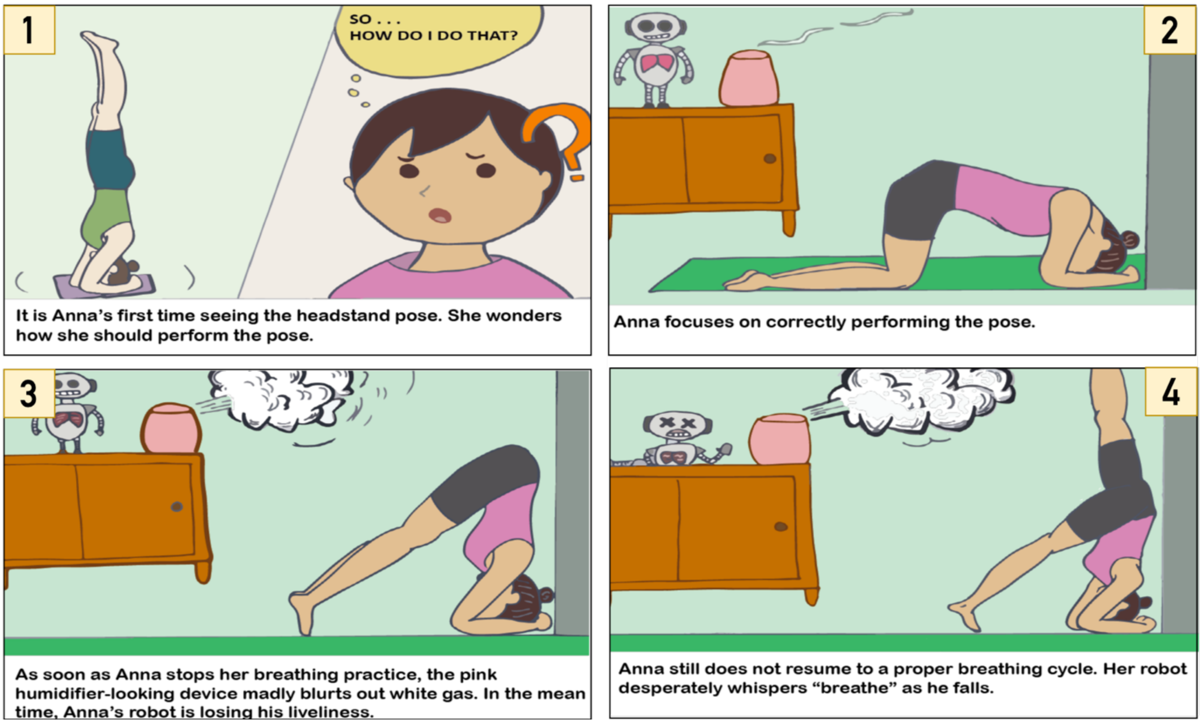
Though the names may not all be enumerated, I humbly extend my sincerest gratitude to all the people who have shared the effort and knowledge in any manner for this research.

APPENDIX A

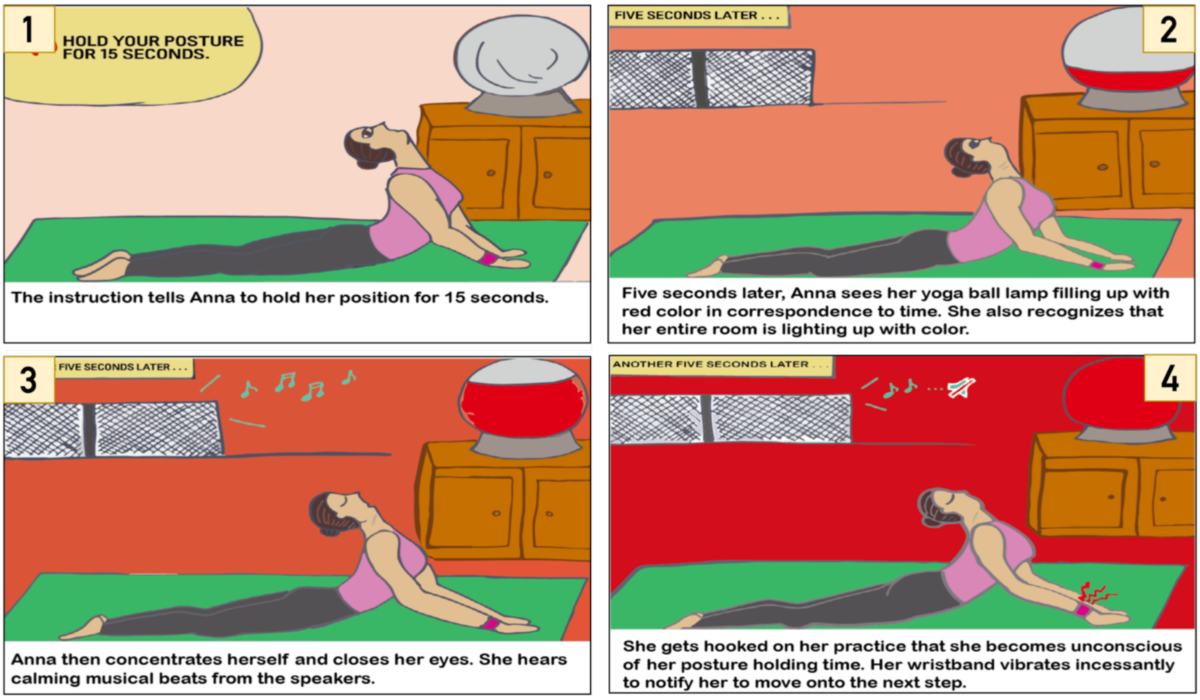
1. Breathing Training



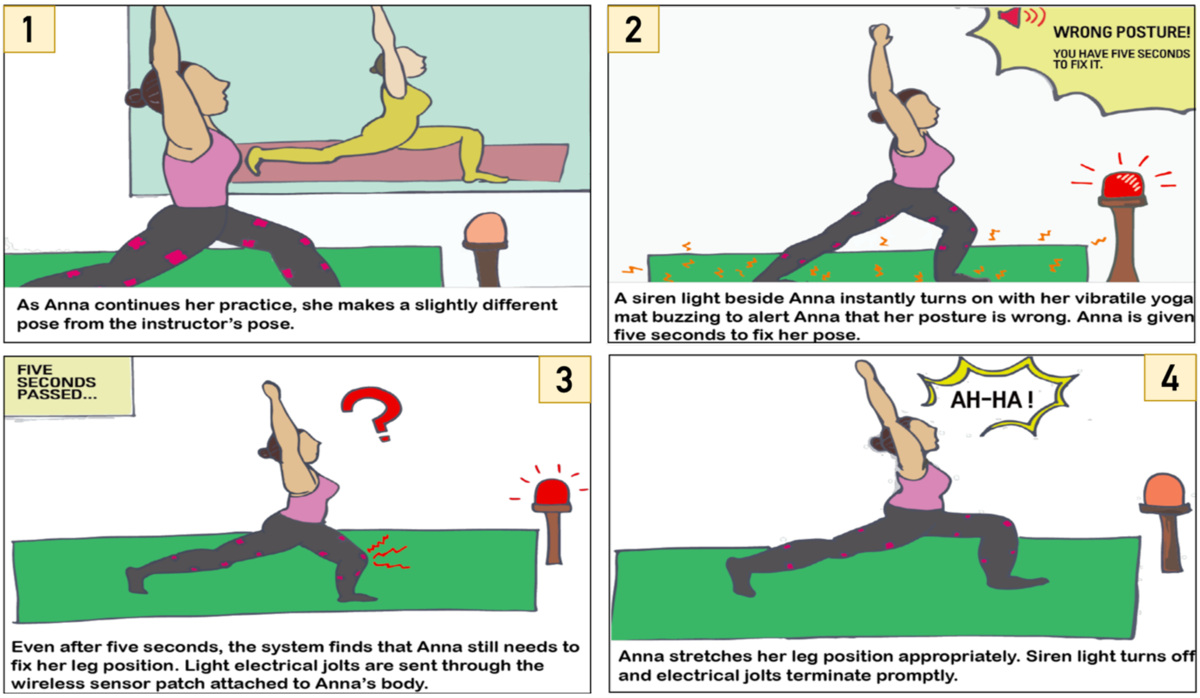
2. Breathing Awareness



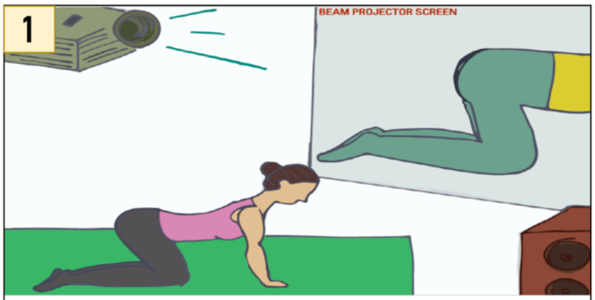
3. Holding Time



4. Wrong Posture Alert

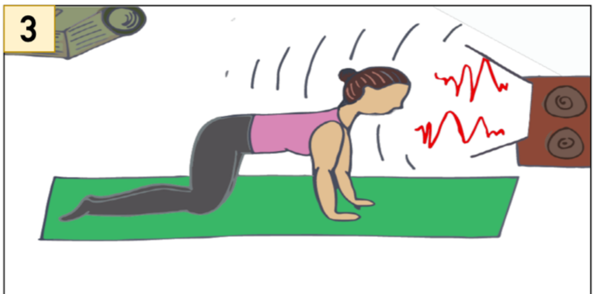


5. Posture Guidance



Anna starts her practice by following the pose steps shown in her beam projector screen.

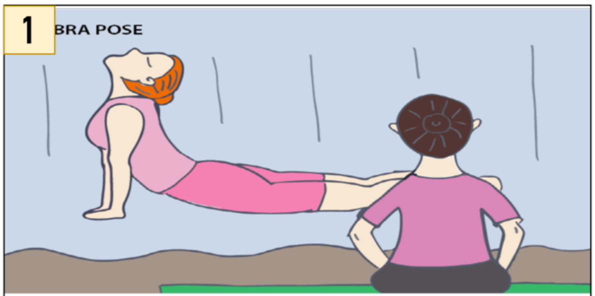
She hears some advice auditorily, and looks up at the screen. She sees how to fix her pose by lifting up her hips so that they line up with her knees.



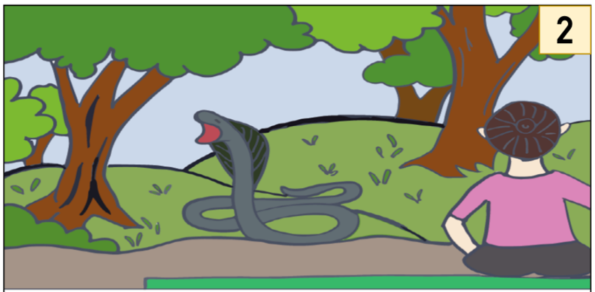
As Anna starts to fix her pose, she hears high pitched noise from the speakes.

As soon as Anna fixed her pose correctly, the high pitched noise diminished. She then receives a 'GOOD' sign for her pose.

6. Harmonious Learning

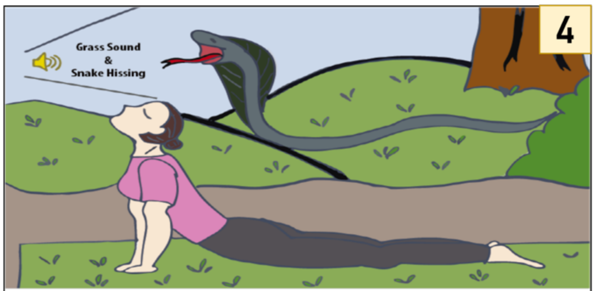


Anna practices in a curtained room. She sees instructor's 'cobra pose' on the curtain.



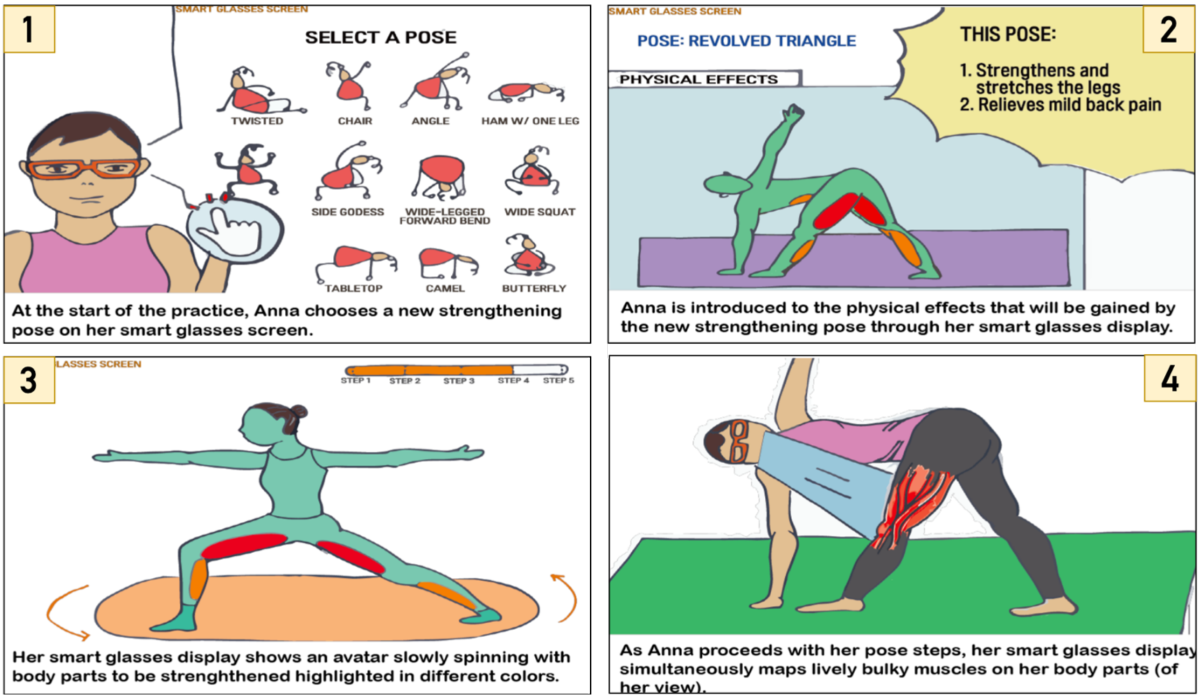
The curtain suddenly changes its display to show a cobra in a forest.

As Anna starts to pose, her yoga mat changes its appearance as grassy. Anna can also feel the freshness and roughness of grass from her yoga mat.

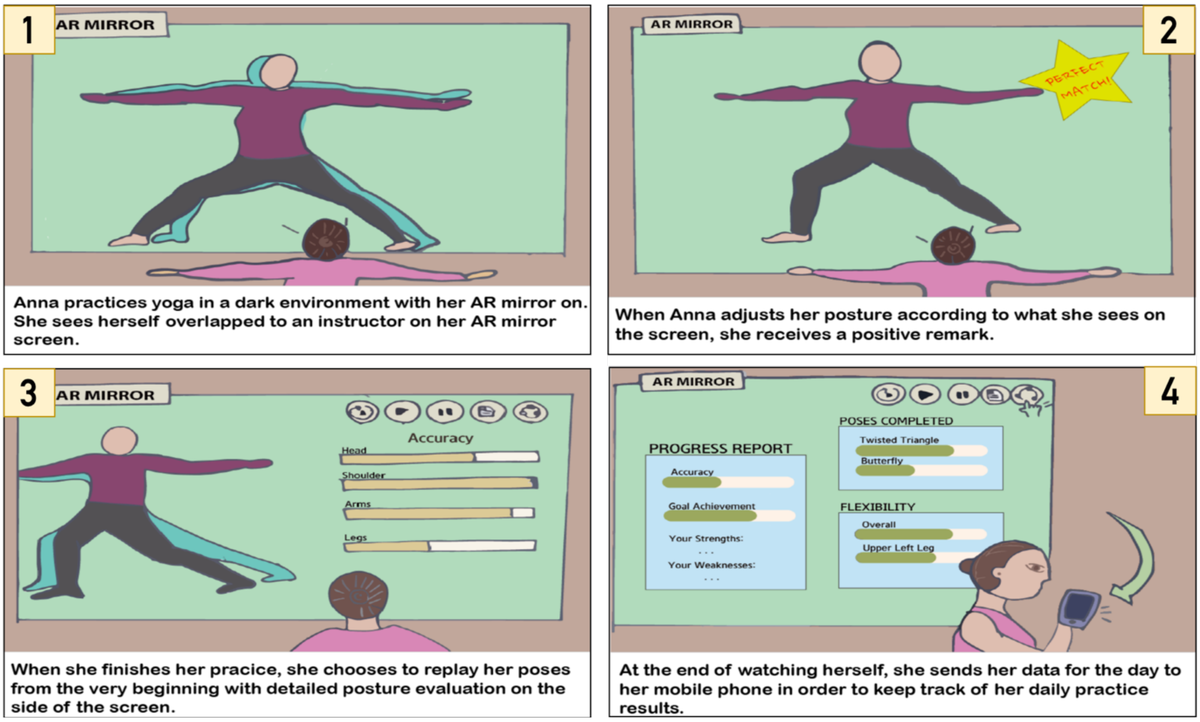


Anna closes her eyes and imagines as if she was a cobra in nature. As she harmnoizes herself into nature, she hears sound of grass and hissing snakes.

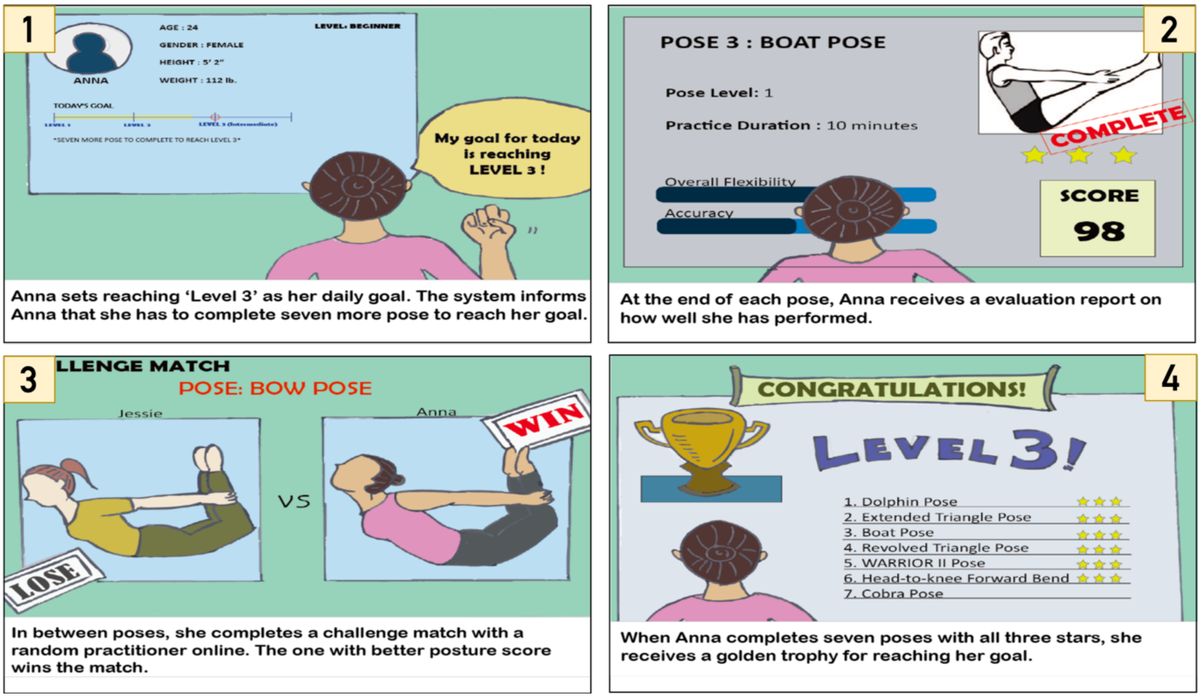
7. Physical Effects



8. Self-Monitoring



9. Game Design Elements



APPENDIX B

All Poses

	TP Rate	FP Rate	Precision	Recall	F-Measure	Class
Sub 01	0.391	0.086	0.604	0.391	0.475	Inhale
53.9879%	0.365	0.062	0.664	0.365	0.471	RetentionIn
	0.804	0.304	0.469	0.804	0.592	Exhale
	0.598	0.162	0.551	0.598	0.574	RetentionEx
	0.540	0.153	0.572	0.540	0.528	Weighted Avg.
Sub 02	0.860	0.023	0.926	0.860	0.891	Inhale
89.1609%	0.922	0.081	0.791	0.922	0.851	RetentionIn
	0.891	0.017	0.945	0.891	0.918	Exhale
	0.893	0.023	0.928	0.893	0.910	RetentionEx
	0.892	0.036	0.898	0.892	0.893	Weighted Avg.
Sub 03	0.640	0.127	0.622	0.640	0.631	Inhale
72.0169%	0.826	0.133	0.675	0.826	0.743	RetentionIn
	0.821	0.040	0.873	0.821	0.846	Exhale
	0.592	0.072	0.734	0.592	0.655	RetentionEx
	0.720	0.093	0.726	0.720	0.719	Weighted Avg.
Sub 04	0.611	0.142	0.587	0.611	0.599	Inhale
58.2899%	0.519	0.126	0.578	0.519	0.547	RetentionIn
	0.487	0.193	0.456	0.487	0.471	Exhale
	0.713	0.095	0.718	0.713	0.715	RetentionEx
	0.583	0.139	0.585	0.583	0.583	Weighted Avg.
Sub 05	0.982	0.097	0.768	0.982	0.862	Inhale
73.2058%	0.688	0.102	0.696	0.688	0.692	RetentionIn
	0.709	0.122	0.662	0.709	0.685	Exhale
	0.553	0.037	0.833	0.553	0.665	RetentionEx
	0.732	0.089	0.739	0.732	0.725	Weighted Avg.
Sub 06	0.845	0.045	0.845	0.853	0.806	Inhale
77.4083%	0.687	0.142	0.614	0.687	0.649	RetentionIn
	0.761	0.085	0.749	0.761	0.851	Exhale
	0.803	0.029	0.905	0.803	0.851	RetentionEx
	0.774	0.075	0.783	0.774	0.777	Weighted Avg.
Sub 07	0.668	0.203	0.521	0.668	0.585	Inhale
61.0957%	0.630	0.141	0.599	0.630	0.614	RetentionIn
	0.687	0.066	0.776	0.687	0.729	Exhale
	0.459	0.108	0.587	0.459	0.515	RetentionEx
	0.611	0.130	0.621	0.611	0.611	Weighted Avg.
Sub 08	0.726	0.016	0.935	0.726	0.817	Inhale
75.0833%	0.915	0.175	0.635	0.915	0.750	RetentionIn
	0.650	0.043	0.837	0.650	0.732	Exhale
	0.713	0.099	0.711	0.713	0.712	RetentionEx
	0.751	0.083	0.779	0.751	0.752	Weighted Avg.
Sub 09	0.391	0.157	0.448	0.391	0.418	Inhale
52.5596%	0.608	0.091	0.691	0.608	0.647	RetentionIn
	0.442	0.116	0.563	0.442	0.495	Exhale
	0.657	0.269	0.451	0.657	0.535	RetentionEx
	0.526	0.158	0.539	0.526	0.524	Weighted Avg.
Sub 10	0.831	0.073	0.790	0.831	0.810	Inhale
80.0676%	0.815	0.066	0.802	0.815	0.808	RetentionIn
	0.787	0.045	0.854	0.787	0.819	Exhale
	0.770	0.082	0.763	0.770	0.767	RetentionEx
	0.801	0.067	0.802	0.801	0.801	Weighted Avg.

Easy Pose

	TP Rate	FP Rate	Precision	Recall	F-Measure	Class
Sub 01	0.345	0.172	0.390	0.345	0.366	Inhale
59.8581%	0.800	0.1152	0.687	0.800	0.739	RetentionIn
	0.675	0.044	0.843	0.675	0.750	Exhale
	0.571	0.204	0.495	0.571	0.531	RetentionEx
	0.599	0.133	0.606	0.599	0.598	Weighted Avg.
Sub 02	0.929	0.016	0.949	0.929	0.938	Inhale
94.2098%	0.993	0.046	0.881	0.993	0.934	RetentionIn
	0.893	0.000	1.000	0.893	0.944	Exhale
	0.953	0.016	0.953	0.953	0.953	RetentionEx
	0.942	0.019	0.946	0.942	0.942	Weighted Avg.
Sub 03	0.811	0.010	0.960	0.811	0.879	Inhale
92.3356%	0.989	0.045	0.872	0.989	0.927	RetentionIn
	1.000	0.022	0.943	1.000	0.970	Exhale
	0.890	0.025	0.927	0.890	0.908	RetentionEx
	0.923	0.025	0.926	0.923	0.922	Weighted Avg.
Sub 04	0.523	0.094	0.640	0.523	0.575	Inhale
69.0008%	0.835	0.090	0.758	0.835	0.795	RetentionIn
	0.536	0.125	0.594	0.536	0.536	Exhale
	0.861	0.105	0.734	0.861	0.792	RetentionEx
	0.690	0.104	0.682	0.690	0.682	Weighted Avg.
Sub 05	0.926	0.040	0.884	0.9263	0.904	Inhale
85.8968%	0.733	0.034	0.880	0.733	0.800	RetentionIn
	0.933	0.070	0.818	0.933	0.872	Exhale
	0.845	0.045	0.862	0.845	0.853	RetentionEx
	0.859	0.047	0.861	0.857	0.857	Weighted Avg.
Sub 06	0.950	0.042	0.881	0.950	0.914	Inhale
84.4743%	0.814	0.094	0.741	0.814	0.776	RetentionIn
	0.856	0.058	0.826	0.856	0.850	Exhale
	0.764	0.012	0.958	0.764	0.850	RetentionEx
	0.845	0.051	0.853	0.845	0.845	Weighted Avg.
Sub 07	0.812	0.150	0.639	0.812	0.715	Inhale
63.5391%	0.779	0.156	0.626	0.779	0.694	RetentionIn
	0.547	0.033	0.845	0.547	0.664	Exhale
	0.407	0.146	0.483	0.407	0.442	RetentionEx
	0.635	0.122	0.648	0.635	0.628	Weighted Avg.
Sub 08	0.954	0.006	0.981	0.954	0.967	Inhale
96.5814%	0.958	0.009	0.974	0.958	0.966	RetentionIn
	0.992	0.017	0.952	0.992	0.971	Exhale
	0.958	0.014	0.958	0.958	0.958	RetentionEx
	0.966	0.012	0.966	0.966	0.966	Weighted Avg.
Sub 09	0.872	0.424	0.392	0.872	0.541	Inhale
	0.277	0.006	0.936	0.277	0.427	RetentionIn
	0.131	0.004	0.913	0.131	0.230	Exhale
	0.787	0.211	0.560	0.787	0.655	RetentionEx
	0.512	0.157	0.705	0.512	0.462	Weighted Avg.
Sub 10	1.000	0.009	0.973	1.000	0.987	Inhale
	0.864	0.011	0.960	0.864	0.909	RetentionIn
	0.917	0.044	0.880	0.917	0.898	Exhale
	0.983	0.015	0.959	0.983	0.971	RetentionEx
	0.941	0.020	0.942	0.941	0.941	Weighted Avg.

Downward-Facing Dog Pose

	TP Rate	FP Rate	Precision	Recall	F-Measure	Class
Sub 01	0.869	0.136	0.672	0.869	0.758	Inhale
63.5017%	0.697	0.197	0.532	0.697	0.603	RetentionIn
	0.560	0.110	0.622	0.560	0.589	Exhale
	0.436	0.040	0.800	0.436	0.565	RetentionEx
	0.635	0.119	0.660	0.635	0.627	Weighted Avg.
Sub 02	1.000	0.000	1.000	1.000	1.000	Inhale
97.7716%	0.978	0.019	0.946	0.978	0.961	RetentionIn
	0.933	0.007	0.977	0.933	0.955	Exhale
	1.000	0.004	0.989	1.000	0.994	RetentionEx
	0.978	0.007	0.978	0.978	0.978	Weighted Avg.
Sub 03	0.400	0.505	0.199	0.400	0.266	Inhale
32.9304%	0.233	0.084	0.466	0.233	0.311	RetentionIn
	0.071	0.072	0.259	0.071	0.111	Exhale
	0.612	0.229	0.485	0.612	0.541	RetentionEx
	0.329	0.219	0.353	0.329	0.308	Weighted Avg.
Sub 04	0.355	0.073	0.592	0.355	0.444	Inhale
38.6641%	0.353	0.344	0.260	0.353	0.299	RetentionIn
	0.386	0.256	0.345	0.386	0.364	Exhale
	0.449	0.150	0.509	0.449	0.477	RetentionEx
	0.387	0.209	0.422	0.387	0.395	Weighted Avg.
Sub 05	0.685	0.101	0.680	0.685	0.683	Inhale
62.5119%	0.595	0.133	0.588	0.595	0.591	RetentionIn
	0.592	0.140	0.602	0.592	0.597	Exhale
	0.632	0.127	0.633	0.632	0.633	RetentionEx
	0.625	0.126	0.625	0.625	0.625	Weighted Avg.
Sub 06	0.540	0.119	0.574	0.540	0.557	Inhale
43.1193%	0.320	0.119	0.444	0.320	0.372	RetentionIn
	0.741	0.388	0.410	0.741	0.528	Exhale
	0.133	0.139	0.267	0.133	0.178	RetentionEx
	0.431	0.196	0.416	0.431	0.402	Weighted Avg.
Sub 07	0.620	0.094	0.681	0.620	0.649	Inhale
58.5868%	0.590	0.156	0.551	0.590	0.570	RetentionIn
	0.370	0.046	0.725	0.370	0.490	Exhale
	0.750	0.260	0.511	0.750	0.608	RetentionEx
	0.586	0.141	0.615	0.586	0.580	Weighted Avg.
Sub 08	0.967	0.022	0.935	0.967	0.951	Inhale
92.6575%	0.944	0.047	0.867	0.944	0.904	RetentionIn
	0.921	0.018	0.943	0.921	0.932	Exhale
	0.879	0.011	0.967	0.879	0.921	RetentionEx
	0.927	0.024	0.929	0.927	0.927	Weighted Avg.
Sub 09	0.744	0.022	0.917	0.744	0.822	Inhale
61.2601%	0.867	0.294	0.497	0.867	0.631	RetentionIn
	0.400	0.063	0.679	0.400	0.503	Exhale
	0.438	0.137	0.514	0.438	0.473	RetentionEx
	0.613	0.129	0.652	0.613	0.608	Weighted Avg.
Sub 10	0.600	0.215	0.460	0.600	0.521	Inhale
68.1333%	0.914	0.031	0.901	0.914	0.908	RetentionIn
	0.747	0.032	0.894	0.747	0.814	Exhale
	0.481	0.146	0.543	0.481	0.510	RetentionEx
	0.681	0.105	0.701	0.681	0.687	Weighted Avg.

Tree Pose

	TP Rate	FP Rate	Precision	Recall	F-Measure	Class
Sub 01	0.967	0.212	0.581	0.967	0.726	Inhale
55.7989%	0.433	0.263	0.332	0.433	0.376	RetentionIn
	0.767	0.100	0.697	0.767	0.730	Exhale
	0.179	0.000	1.000	0.179	0.304	RetentionEx
	0.558	0.134	0.677	0.558	0.518	Weighted Avg.
Sub 02	0.945	0.036	0.897	0.945	0.920	Inhale
91.3005%	0.844	0.053	0.837	0.844	0.840	RetentionIn
	0.900	0.021	0.934	0.900	0.917	Exhale
	0.958	0.006	0.983	0.958	0.970	RetentionEx
	0.913	0.028	0.914	0.913	0.913	Weighted Avg.
Sub 03	0.429	0.013	0.911	0.429	0.583	Inhale
58.6575%	0.752	0.364	0.413	0.752	0.533	RetentionIn
	0.868	0.178	0.626	0.868	0.727	Exhale
	0.287	0.000	1.000	0.287	0.446	RetentionEx
	0.587	0.141	0.735	0.587	0.572	Weighted Avg.
Sub 04	0.922	0.081	0.782	0.922	0.847	Inhale
78.9698%	0.695	0.096	0.701	0.695	0.698	RetentionIn
	0.676	0.033	0.878	0.676	0.764	Exhale
	0.870	0.070	0.812	0.870	0.840	RetentionEx
	0.790	0.069	0.795	0.790	0.787	Weighted Avg.
Sub 05	0.964	0.077	0.804	0.964	0.877	Inhale
70.4384%	0.286	0.000	1.000	0.286	0.444	RetentionIn
	0.547	0.033	0.845	0.547	0.664	Exhale
	1.000	0.289	0.551	1.000	0.547	RetentionEx
	0.704	0.103	0.796	0.704	0.675	Weighted Avg.
Sub 06	0.827	0.078	0.764	0.827	0.794	Inhale
77.6065%	0.783	0.169	0.615	0.783	0.689	RetentionIn
	0.782	0.049	0.845	0.782	0.812	Exhale
	0.717	0.003	0.989	0.717	0.831	RetentionEx
	0.776	0.075	0.804	0.776	0.781	Weighted Avg.
Sub 07	0.689	0.085	0.713	0.689	0.701	Inhale
76.1413%	0.837	0.132	0.684	0.837	0.753	RetentionIn
	0.829	0.024	0.923	0.829	0.874	Exhale
	0.685	0.077	0.754	0.685	0.718	RetentionEx
	0.761	0.079	0.769	0.761	0.762	Weighted Avg.
Sub 08	0.888	0.512	0.350	0.888	0.502	Inhale
33.7262%	0.291	0.116	0.435	0.291	0.349	RetentionIn
	0.167	0.061	0.497	0.167	0.250	Exhale
	0.056	0.189	0.096	0.056	0.071	RetentionEx
	0.337	0.214	0.342	0.337	0.285	Weighted Avg.
Sub 09	0.636	0.224	0.485	0.636	0.550	Inhale
51.5327%	0.654	0.160	0.577	0.654	0.613	RetentionIn
	0.369	0.152	0.448	0.369	0.405	Exhale
	0.403	0.111	0.548	0.403	0.465	RetentionEx
	0.515	0.162	0.515	0.508	0.354	Weighted Avg.
Sub 10	0.960	0.013	0.960	0.960	0.960	Inhale
86.5366%	0.879	0.071	0.799	0.879	0.837	RetentionIn
	0.730	0.062	0.793	0.730	0.760	Exhale
	0.890	0.033	0.907	0.890	0.898	RetentionEx
	0.865	0.044	0.866	0.865	0.865	Weighted Avg.

Pose Classifier Performances

	TP Rate	FP Rate	Precision	Recall	F-Measure
Sub 01	1.000	0.000	1.000	1.000	1.000
Sub 02	1.000	0.000	1.000	1.000	1.000
Sub 03	0.959	0.013	0.959	0.959	0.959
Sub 04	0.854	0.068	0.854	0.854	0.852
Sub 05	0.971	0.012	0.973	0.971	0.971
Sub 06	0.998	0.001	0.998	0.998	0.998
Sub 07	0.999	0.000	0.999	0.999	0.999
Sub 08	0.997	0.001	0.997	0.997	0.997
Sub 09	0.999	0.001	0.999	0.999	0.999
Sub 10	1.000	1.000	1.000	1.000	1.000