Increasing Access to Trainer-led Aerobic Exercise for People with Visual Impairments through a Sensor Mat System

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ABSTRACT

People with visual impairments (PVIs) are less likely to participate in physical activity than their sighted peers. One barrier is the lack of accessible group-based aerobic exercise classes, often due to instructors not giving accessible verbal instructions. While there is research in exercise tracking, these tools often require vision or familiarity with the exercise. There are accessible solutions that give personalized verbal feedback in slower-paced exercises, not generalizing to aerobics. In response, we have developed an algorithm that detects shoeprints on a sensor mat using computer vision and a CNN. We can infer whether a person is following along with a step aerobics workout and are designing reactive verbal feedback to guide the person to rejoin the class. Future work will include finishing development and conducting a user study to assess the effectiveness of the reactive verbal feedback.

CCS CONCEPTS

• **Human-centered computing** → Accessibility; Accessibility systems and tools.

KEYWORDS

People with visual impairments, Exercise tracking, Sensor mat, Convolutional neural network

ACM Reference Format:
Jeehan Malik, Mitchell Majure, Hana Gabrielle Rubio Bidon, Regan Lamoureux, and Kyle Rector. 2021. Increasing Access to Trainer-led Aerobic Exercise for People with Visual Impairments through a Sensor Mat System. In *The 23rd International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS '21), October 18–22, 2021, Virtual Event, USA*. ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3441852.3476557

1 INTRODUCTION

People with visual impairments (PVIs) are less likely to participate in physical activity than their sighted peers [4, 5, 11, 12]. Healthy People 2020 lists inclusion of people with disabilities in health promotion as a priority [3]. Mainstream exercise classes provide opportunities to perform physical activity but are not accessible because instructors speak phrases based on the premise that the person is sighted [15], and cues provided by mirrors are visual. In prior work, we used Microsoft Kinect's body tracking to develop and empirically evaluate a personalized in-home yoga system for PVIs [13], while others developed modified videogames [8, 9] for fast-paced in-home exercise. Nevertheless, barriers still exist for group-based aerobic exercise, and PVIs are open to technology that provides assistance [14]. The technology should be portable and intrude the exercise class as little as possible to increase practicality. The main technical challenge is how to use less intrusive, portable tracking technologies (e.g., sensor mat) to measure synchrony with an instructor in aerobic exercises.

Researchers have developed wearable technologies to recognize aerobic exercises. Chan et al. [1] used a body worn camera and a Random Decision Forest classifier to detect a wider range of AEs (20 exercises) in an aerobic workout routine. Morris et al. [10] developed a general-purpose activity recognizer, RecoFit, an arm-worn sensor and detects exercises by utilizing the fact that they are repetitive. The authors assumed that the target audience had familiarity with the exercises, so it may not detect exercises that are performed incorrectly. Šeketa et al. used an accelerometer and magnetometer to visually show a person whether they are performing the exercise correctly by having the user compare their visual avatar to a "coach" avatar but did not provide feedback about why they are performing the exercise incorrectly [16]. Our research does not assume how much a person knows about an exercise. If a participant is not in sync, we want to analyze this through sensors instead of a person visually comparing themselves with others.

Gasperetti et al. explored how to make Dance Dance Revolution accessible to youth with visual impairments. They modified the game for youth with visual impairments, including them being in closer proximity to the screen, increasing visual contrast of the game elements, and decreasing the pace of the game. For youth who were totally blind, they required more verbal cueing and practice [2]. While these technology solutions increase access to exercise to people who are blind, they do not provide the ability to exercise in a group activity. While our proposed research is not specifically an exergame, our research will generalize to exergame accessibility where the objective of the game includes mimicking body movements that are presented on the screen (e.g., dancing exergames).

ASSETS '21, October 18–22, 2021, Virtual Event, USA

ACM ISBN 978-1-4503-8306-6/21/10.
https://doi.org/10.1145/3441852.3476557

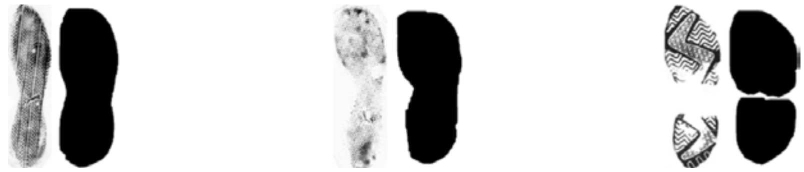

Figure 1: Original photos for three shoes from the footwear impression database alongside the filled in shoeprints after applying morphological operations. Original shoeprints come from a publicly available dataset by Adam Kortylewski [6, 7].

This project aims to make aerobic exercises more accessible to people with visual impairments (PVIs) through a novel technology design. We are developing an algorithm with a pressure sensor mat to determine whether a person is in sync with a step aerobics class. We interpret the mat's readings with computer vision and a convolutional neural network (CNN) to infer each shoe and its location. We chose a CNN over machine learning approaches to avoid identifying features. We want to determine the effect of feedback (to address a person falling out of sync) on the ability of PVIs to be in sync with an aerobics class. We are exploring this concept with a prerecorded step aerobics workout video.

2 TRAINING AND VALIDATING CNN FOR DETECTING LEFT AND RIGHT SHOEPRINTS

To create training data, we collected 24,400 shoeprints from 12 individuals, all wearing athletic shoes with brands: Adidas, Nike, and Skechers, and sizes: 7 (W), 7.5 (W) and 8-12 (M). We had these individuals march on a sensor mat (Sensing Tex Fitness Mat Dev Kit [17]) while standing at different points on the mat: 25%, 50%, and 75% of the mat's width. We automatically labeled the images as right and left using the shoeprint's x-coordinate on the mat.

To prevent our CNN from overfitting, we also trained with an existing footwear impression database [7]. First, we resized the shoeprints to ~350x750 pixels to make the dataset consistent. Starting from 1,174 right shoeprints, we manually edited 446 shoeprints to remove rulers and non-shoe artifacts. Then, we applied morphological operations [18] to convert the highly detailed shoeprints to be black and white, which closely resembles our other training data. First, we eroded the boundary, opened (erosion followed by dilation) to remove noise, blurred to reduce features, and eroded the boundary again. See Figure 1 for before and after photos. The footwear impression database only had right shoeprints, so we reflected these shoeprints by 180° on the vertical axis to train them as left shoeprints. We trained all shoeprints between at randomly sampled angles between -90° and +90° for both left and right shoes.

To validate our CNN, we conducted 5-fold cross validation. For all folds, the average accuracy was 97.25% (+/- 0.06%) with 0.1 loss, and the precision and recall were 0.97. This will contribute to a dependable system, and therefore to better user evaluations. Our CNN is not reliable with partial shoeprints, so we only use readings with high confidence (≥0.9).

3 WORKOUT DETECTION ALGORITHM

We implemented an algorithm that compares the "shoeprint status" with a "workout specification." If there are 3 missteps (or no matches over three beats of the workout), then our system will deliver reactive verbal feedback.

3.1 Shoeprint Status

The "shoeprint status" comprises getting information about each shoe's position and rotation. We capture a sensor mat image, extract shoeprints, and analyze the bounding boxes. For shoeprints that are in the top 2/3 of the mat (and therefore complete), we run them through the CNN. The sensor mat readings are closed source, so we screen capture the mat software's output image, which shows pressure data in color (see Figure 2 #1).

To extract two separate shoeprints from the screen capture, we have a two-step process. First, we convert the image to grayscale and apply blur (Figure 2 #2). Second, we find the image's contours (i.e., a curve joining all continuous points along a boundary with similar color) and pick the contours with the two largest areas that do not overlap (Figure 2 #3). We explored contour extraction with RGB/HSV masking, but grayscale image thresholding gave the best result.

To find the position of each shoe, we analyze the bounding box around the shoe's contour. We determine whether the shoe is on the "block" (or upper 2/3 of the mat), the "floor" (or lower 1/3 of the mat), or off the mat altogether. We identify the angle and position of the foot because step aerobics exercises require the feet to move to specified locations with a specified rotation (see Figure 3).

- If the shoe is "on block," we determine the shoe's rotation to the nearest multiple of 45° using a polynomial interpolation of the height to width ratio of the bounding box. We classify whether it is left or right by applying the CNN and picking the highest level of confidence if it is ≥0.9. Otherwise, we disregard the reading.
- If the shoe is on the "floor," we do not determine its angle. We assign left or right by comparing its bounding box position to the other. If there is only one contour, then we consult the prior bounding boxes and assign the closest.

The latency from receiving the mat reading to updating the status is 75-95 milliseconds (ms) on an Intel(R) Core(TM) i7-8650U CPU @ 1.90GHz, 2.11 GHz, 8GB RAM and 60-70 ms on an NVIDIA GeForce RTX 3070 Laptop GPU, 8GB RAM.

3.2 Workout Specification

We selected two portions of a workout, Beginner Step Aerobics Quick Cardio Workout at Home Fitness by Jenny Ford [19]; the first 6:58 minutes and final 4:55 minutes, both 130 beats per minute. A workout specification includes the moves broken down to each "step," number of repetitions of each move, which we save as csv

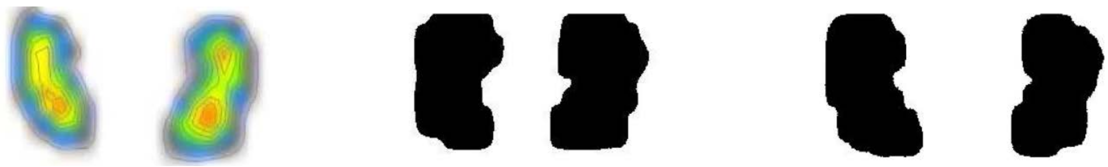

Figure 2: 1) mat reading; 2) original mat photo in black and white; 3) separated shoes to send to the CNN individually.

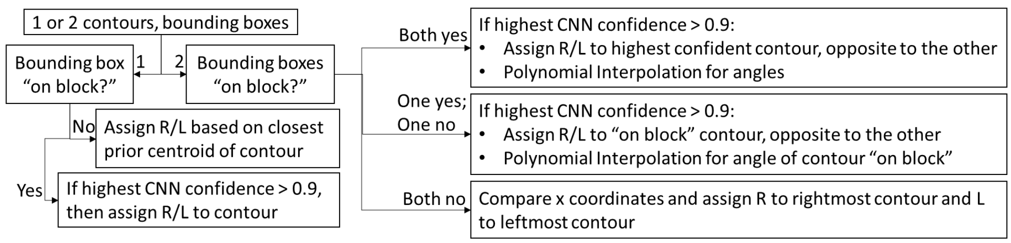

Figure 3: Flowchart of how we assign whether each contour is a right or left foot and the angle.

files. We are still testing whether the "mat status" matches the "workout specification" with a perfectly performed workout. Thus far, we learned that at each beat we should check the status of only one foot, as the other foot is actively moving.

4 PRELIMINARY REACTIVE VERBAL FEEDBACK DESIGN AND FUTURE WORK

While our system can determine *if* a person needs verbal feedback, a key design question is determining *when it is appropriate* to give feedback. Our system should be compatible with the instructor. Thus, if the system can deliver the verbal feedback before the instructor cues the next move, then it will proceed. Otherwise, it will not give feedback and defer to the instructor, allowing the instructor to prepare for the next move. The system will give timed verbal feedback to each beat, stating each step required two times, followed by counting the person down to rejoin the workout.

We will complete system development and evaluate the effectiveness of our reactive feedback through user studies. We hope our findings inform design guidelines for technologies that give exercise or body movement instructions. These will specifically help PVIs, but also people who cannot see a visual instruction for other reasons (e.g., head pointed away from screen, chose not to have visuals). These findings will contribute to the body of research in Accessibility, Human-Computer Interaction, and more specifically those who develop exercise games or spatial interfaces.

ACKNOWLEDGMENTS

This work is supported in part by National Science Foundation grants IIS-1849822 and CNS-2050526. Hana Gabrielle Bidon participated in the Distributed Research Experiences for Undergraduates (DREU) program, a joint project of the CRA Committee on Widening Participating in Computing Research (CRA-WP) and the Coalition to Diversify Computing (CDC), funded in part by the NSF Broadening Participation in Computing program (BPC-A-1840724).

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