Poster: Pain-O-Vision, Effortless Pain Management

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ABSTRACT

Chronic pain is often an ongoing challenge for patients to track and collect data. *Pain-O-Vision* is a smartwatch enabled pain management system that uses computer vision to capture the details of painful events from the user. A natural reaction to pain is to clench ones fist. The embedded camera is used to capture different types of fist clenching, to represent different levels of pain. An initial prototype was built on an Android smartwatch that uses a cloud-based classification service to detect the fist clench gestures. Our results show that it is possible to map a fist clench to different levels of pain which allows the patient to record the intensity of a painful event without carrying a specialized pain management device.

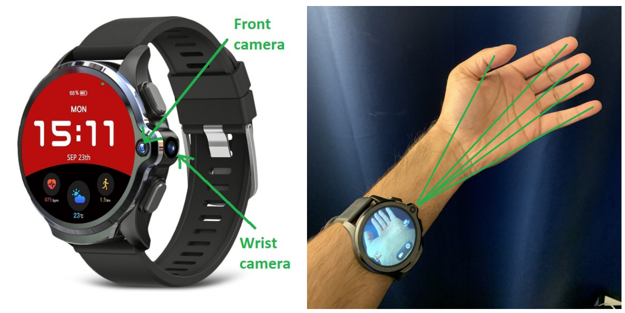

Figure 1: Dual camera smartwatch with palm view

CCS CONCEPTS

• **Human-centered computing** → **Mobile devices**; • **Applied computing** → **Consumer health**.

KEYWORDS

pain management, smartwatches, mobile computing

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1 INTRODUCTION

Chronic pain affects a large subset of society. Pain can be difficult to classify as some people experience it differently from others. Pain management between a patient and their healthcare provider presents challenges with the accuracy in reporting the onset of a painful episode and characterizing the intensity of the pain. When a patient experiences an episode of chronic pain outside a clinical setting, their ability to later recall details about each episode is lost overtime. An often-used data collection method known as Ecological Momentary Assessment (EMA) affords frequent, in-situ assessment of physiological and psychological data to improve recall [3]. Reducing the burden on a patient to manage a medical condition is the goal of this work. Expressions of pain are often manifested as physical reactions, which presents an opportunity for instrumented devices to capture the event with little interaction from the patients.

This work introduces *Pain-O-Vision* for reducing the burden of EMA, leveraging the images captured from the wrist in real-time to classify hand gestures to different pain levels and recording the pain levels in the user's smartwatch application. Previous work [1] has shown that a natural reaction to pain is to squeeze or clench ones fist, but it requires the user to carry a specialized squeezable device in the pocket wherever they go to register the pain event. *Pain-O-Vision* reduces this burden by keeping the user input as discreet as possible using the patient's smartwatch for this purpose. Several works [2, 4–6] have adopted cameras to capture various hand angles from a body-mounted camera for multiple goals, but none of them used the view of the palm and fingers to identify pain events. Hence, this work explores embedded cameras in commodity smartwatches to provide a mobile hands-free experience for EMA of painful events. As shown in Figure 1, our initial prototype leverages the images captured from the wrist in real-time to launch the application without using a second hand, making our approach a one-handed experience[1].

2 *PAIN-O-VISION*

Our prototype relies on the Kospet Prime smartwatch, which is outfitted with two cameras, as seen in Figure 1. The front-facing camera is used for facial unlock, and the side camera captures the input gestures from the wrist. The smartwatch also has several sensors such as the accelerometer and gyroscope that provide gesture-based input.

Pain-O-Vision leverages both the smartwatch and cloud for deploying the software components. The patient interacts with the smartwatch via the camera. The images from the camera are sent

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[1]The current prototype requires wearing the smartwatch in a reversed position, but we envision a camera embedded in the watch band where the patient can capture the images easily.

to the Google AutoML[2] service. The classification is then returned and stored. AutoML is a blackbox image classification service that allows users to use their own datasets to create custom models that can later be invoked as a service running remotely in the Google cloud.

When the patient feels the onset of a painful event and wants to record it using *Pain-O-Vision* , they must first raise the watch to trigger the face unlock feature. After the smartwatch is unlocked, a custom macro implemented in MacroDroid[3] detects the unlock event and launches the *Gesture Listener*. The *Gesture Listener* waits for the patient to perform a hand gesture within a specified time. The hand gesture triggers *Pain-O-Vision* to start a count down for 3 seconds to make a fist clench. Then the *Classification Manager* activates the camera and takes a photo. At this point, the watch sends a haptic response, and the *Pain-O-Vision UI* closes, releasing the user from any further interaction with the device. In the background, the *Classification Manager* coordinates with *Google AutoML* and the *Pain Management Log* to record the result for later review by the patient or their physician.

3 EARLY RESULTS

In this section, we discuss the results of capturing fist clench gestures from the wrist view on the smartwatch and the accuracy of the Google AutoML Vision classifier. The experiments evaluate different gestures and dataset sizes. The image collection process to train the model should not be lengthy because that places a burden on the patient and so large amounts of training data are not expected to be available. We wanted to see the impact on accuracy when using a smaller dataset compared to a larger dataset. This was done to determine if the smart watch and application could be provisioned in a short period of time, for example within the time frame similar to a visit to the doctors office. The dataset was collected using the smartwatch camera worn by a single person in a well lit room. We hope to explore the accuracy with different lighting conditions, skin tones, and backgrounds in the future.

Experimental setup

We define 3 levels of pain (low, medium, high) and map them to 3 types of fist clenches as shown in Figure 2. The intensity of pain is often associated with people clenching their fist harder and longer. Harder clenches result in the fist curling more towards the wrist and this difference in hand position may allow the model to differentiate levels of pain intensity. We then provided 2 labeled datasets consisting of open fists and a closed fists. To evaluate the impact of the dataset size on the accuracy of the model, a larger set with 1,356 images was collected and a smaller set with only 50 images was collected.

Results discussion

Using the larger dataset, the model classified the fist type correctly approximately 66% of the time, but for the smaller dataset only 50% accuracy was observed. The accuracy suffers from the simplicity

Figure 2: 3 fist clench types

of the single model used and therefore a multi model approach similar to MediaPipe[4] might yield better results. The smartwatch's wearing position is also higher than usual and perhaps a watch with a wide-angle lens could be utilized. This would help to reduce the distance for a more natural wearing position while also narrowing the field of view. A narrower field of view would eliminate some of the background to focus more on the hand and therefore potentially improve the accuracy of the fist clench classification. More work is needed to improve the accuracy to make it reliable enough for the healthcare domain.

4 FINAL THOUGHTS

We presented an approach towards reducing the EMA burden on patients with chronic pain. This prototype takes the first step towards using an embedded camera on the wrist to expand what can be detected from a commodity smartwatch. We hope to apply the approach beyond chronic pain to see if it can help manage other health-related conditions.

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[3] https://www.macrodroid.com/
[4] https://google.github.io/mediapipe/solutions/hands.html