July 2023

Use of Data from Physiological Sensors for Automatic Labeling of User Sentiment

n/a

Use of Data from Physiological Sensors for Automatic Labeling of User Sentiment

ABSTRACT

Mobile devices and wearable computers can detect a variety of events to automatically trigger actions. However, it is hard to determine the level of user satisfaction with such automatically triggered actions. This disclosure describes techniques, implemented with user permission, to determine a user’s reaction to automatically triggered actions. Upon the execution of an automatically triggered action, sensors on a wearable device are utilized to measure physiological parameters such as changes in heart rate, blood oxygen concentration, blood pressure, etc., and/or mechanical movements. Physiological and movement data are used to automatically generate ground-truth labels for a triggered action based on the resulting level of user satisfaction. The labeled actions can be used to update machine learning models that trigger automatic actions.

KEYWORDS

- Wearable device
- Physiological sensor
- Physiological signal
- Photoplethysmography (PPG) sensor
- User satisfaction
- Event-triggered action
- Action triggering
- Emotion recognition
- Smartwatch

BACKGROUND

Mobile devices, wearable devices, and Internet-of-things (IoT) devices can, with user permission, detect a variety of user-related events and automatically trigger actions. For example, when a user enters their home, the garage door may open, an alert may be issued, lights may turn on, a favorite musical piece played, the coffee machine may start brewing, etc. However, it is sometimes unclear if the user is happy with such automatically triggered actions. In theory, the user's satisfaction can be gauged using questionnaires. In addition, the satisfaction can be gauged using the camera to assess the user's facial expressions, turning on the microphone to assess the user's tone, etc. if the user permits such access. However, such techniques can be perceived as being invasive and have limited accuracy.

Generally, context-aware or event-triggered actions work optimally when they please the user. However, the feedback is generally missing as to whether the user is pleased or annoyed with the action taken. Even a relatively simple act of turning on the lights can be deemed inappropriate by a user in certain contexts, e.g., if there is someone sleeping in the room.

DESCRIPTION

This disclosure describes techniques to determine a user's reaction, e.g., if the user is satisfied or unsatisfied, to an automatically triggered action. The techniques are implemented with user permission. Users are provided with options to disable measurement of their reaction, disable one or more sensors or data sources, or otherwise set up their preferred configuration settings.

With the user's permission, upon the execution of an automatically triggered action such as turning on of lights upon the user's entry into a room, sensors on a wearable computer such as a smartwatch or other wearable device measure physiological parameters. For example, based on usurp permissions and device capabilities, such parameters can include changes in heart rate, blood oxygen concentration, blood pressure, etc., and/or mechanical movements. Cardiological parameters such as heart rate, blood pressure, and oxygen concentration can be measured by a photoplethysmography (PPG) sensor embedded in the wearable computer. Mechanical movements can be measured by an inertial measurement unit (IMU) embedded in the wearable computer.

Physiological and movement data can provide insights into whether the executed action tangibly affected the user. For example, a lowered heart rate can be associated with a more relaxed, happier state for the user. Sudden arm movement such as an involuntary jerk, as detected by the IMU, can be associated with a negative reaction. In this manner, sensor data captured immediately after an automatically triggered action can be used to determine if the action was effective. The sensor data is captured locally on the user's device and is utilized specifically to determine the user's reaction. The data capture and use is in accordance with specific user configurable settings. If the user permits, the data can optionally be securely transferred (after removal of user-specific information) to a cloud service that updates machine learning models.

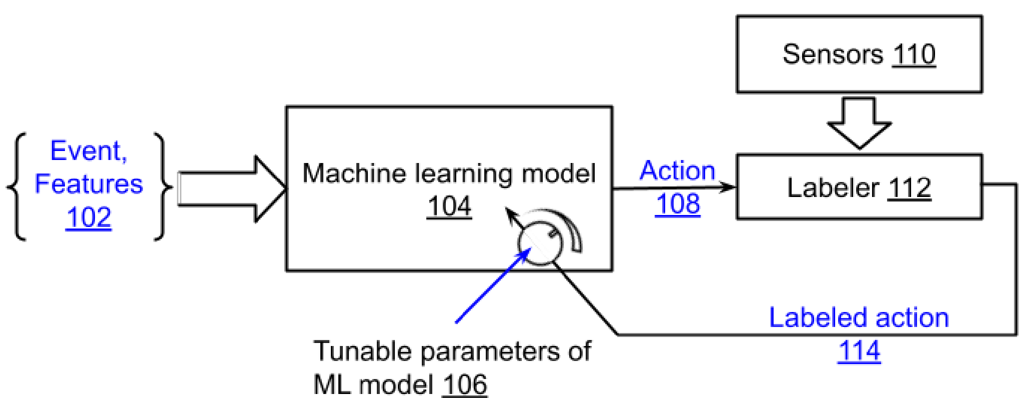

Fig. 1: Using wearable sensor data to update machine learning models that trigger actions

Fig. 1 illustrates using data from wearable sensors to update model(s) that trigger actions. A machine learning (ML) model (104) accepts as input events (e.g., the entry of a user into their home) and features (e.g., time of day) of the event (102) to generate an action (e.g., turning on a light, 108). The ML model can have various tunable parameters (106). Sensors (110) worn by the user generate physiological and mechanical data. The data are attached to the action by a labeler (112) to generate labeled actions (114).

For example, labeled actions can be {‘light turned on’, ‘user happy’}, or {‘light turned on’, ‘user unhappy’}. The labeled actions are used to update the ML model(s) used to generate the actions. The model(s) can be updated either on the user’s device or in the cloud (based on the label, without transfer of the sensor data). If updated on the user’s device, the user’s reactions cause the model(s) to be updated to perform personalized action-triggering functions. If updated in the cloud, e.g., using federated learning (with user permission), action-triggering models that apply to a broad set of users learn parameters based on the users’ reactions. Overall, the described techniques enable event-driven ML models to determine actions that are likely to result in increased user satisfaction or positive reaction.

A variety of signal conditioning procedures can be executed to ensure the robustness of sensor data. Examples of signal conditioning procedures include input and error handling; trace alignment and synchronization; normalization and semantic error handling; etc.

User questionnaires or use of sensors such as a camera or microphone may not be sufficiently accurate to gauge a user’s satisfaction level with particular actions. For example, answers on a questionnaire can be inconclusive (or may not correctly capture a user’s satisfaction level). Also, if a camera or microphone is used to determine satisfaction level based facial expressions or voice tone respectively, the level of change detected by the camera may be inadequate to make an accurate determination of the satisfaction level. Thus, it is difficult to determine a user’s true reactions via a questionnaire, a camera, or a microphone.

Since physiological or mechanical parameters can be measured with good accuracy (and are hard to spoof), the measured values are more likely reflective of user emotion such as calmness or anger in response to a stimulus. Thus, labeling of actions based on such sensor data can be more accurate. In this manner, the described techniques produce automatic and accurate ground-truth labeling of user reactions to actions triggered in response to various events. Furthermore, the labeled actions can be used to tune or to train ML models that generate actions based on various types of events.

In practice, with user permission, a context-aware application can command sensors to detect the user reaction. For example, the application can obtain data from physiological and mechanical sensors for several seconds before and/or after an action. The duration for which the data are obtained can depend on the type of application and the energy budget. The described techniques provide a robust online learning technique that can help a broad range of context aware applications. The techniques can help overcome a key challenge for online learning - the inability to accurately label the data used for training.

The techniques provide a general mechanism that can take a number of low-level inputs such as detected emotion, physiological parameters, etc. and can produce higher level descriptors of a user’s state such as “satisfied, “happy,” “engaged,” etc. and can be used to adjust action triggering to provide refined user-centric capabilities. Also, while the foregoing description refers to events and corresponding actions, the techniques can be utilized to sense the user’s satisfaction over a longer period of time such as over several hours, days, or even weeks, based on aggregated measurements rather than measurement of instantaneous reactions. The techniques can also be used to test how updates to particular features may affect user satisfaction.

Further to the descriptions above, a user may be provided with controls allowing the user to make an election as to both if and when systems, programs, or features described herein may enable the collection of user information (e.g., information about a user's devices, sensor data detected by user devices, social network, social actions or activities, profession, a user's preferences, or a user's current location), and if the user is sent content or communications from a server. In addition, certain data may be treated in one or more ways before it is stored or used so that personally identifiable information is removed. For example, a user's identity may be treated so that no personally identifiable information can be determined for the user, or a user's geographic location may be generalized where location information is obtained (such as to a city, ZIP code, or state level) so that a particular location of a user cannot be determined. Thus, the user may have control over what information is collected about the user, how that information is used, and what information is provided to the user.

CONCLUSION

This disclosure describes techniques, implemented with user permission, to determine a user's reaction to automatically triggered actions. Upon the execution of an automatically triggered action, sensors on a wearable device are utilized to measure physiological parameters such as changes in heart rate, blood oxygen concentration, blood pressure, etc., and/or mechanical movements. Physiological and movement data are used to automatically generate ground-truth labels for a triggered action based on the resulting level of user satisfaction. The labeled actions can be used to update machine learning models that trigger automatic actions.

REFERENCES

[1] Faaborg, Alexander, Gabriel Aaron Cohen, and Austin Robison. “Determining user response to notifications based on a physiological parameter.” U.S. Patent Application 14/244,514 filed April 3, 2014.

[2] Petersen, Morten Just, Joao Paulo Gil de Paiva, Emmet Connolly, and Tim Carlo Jorges. “Determining information flow using physiological parameters.” U.S. Patent Application 14/147,323 filed January 3, 2014.