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Techniques for Detecting and Classifying User Behavior Through the Fusion of Ultrasonic Proximity Data and Doppler-Shift Velocity Data

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Abstract:

This publication describes techniques relating to the detection and classification of user behavior through the fusion of ultrasonic proximity data and Doppler-shift velocity data on a computing device. Through the use of an ultrasonic proximity sensor and, in aspects, a radar sensor, user position and velocity can be combined and analyzed by the computing device to provide accurate user behavior predictions. These user behavior predictions may be used by the computing device to identify unique user behavior features and perform actions based on user behavior identification.

Keywords:

user behavior, user activity, radar sensor, ultrasonic proximity sensor, Doppler, Doppler Shift, machine learning, model, Convolution Neural Network (CNN), ultrasonic sensing, velocity

Background:

User behavior (e.g., user activity) can be detected by a sensor of a computing device (e.g., smartphone, smart home controller) and utilized to enable helpful features (e.g., preserving battery power, opening applications based on user behavior). The utilization of existing hardware sensors for such detection is preferred in order to decrease costs. An ultrasonic proximity sensor in a typical computing device may be utilized to detect user position, however it may also detect other movement within the sensor range (e.g., a moving ceiling fan, pet). Additionally, a radar sensor in a typical computing device may be used to detect velocity, however the Doppler radar frequencies are often noisy, which can lead to inaccurate readings.

The combined use of both Doppler-shift velocity data and ultrasonic proximity data may be used to reduce inaccuracies and inconsistencies of user behavior detection, and further allow for more detailed and unique user behavior detection.

Description:

This publication describes techniques, implemented on a computing device (e.g., a smartphone, a smart watch device, smart home controller), directed to the detection and classification of user behavior (e.g., activity, movement, exercise, gesture, action) through the fusion of ultrasonic proximity data and Doppler-shift velocity data. An example computing device includes a processor, sensors (e.g., a radar sensor, an ultrasonic proximity sensor), an input/output (I/O) device (e.g., a display, a speaker, a microphone), and a computer-readable medium (CRM) that stores device data (e.g., a computer program module).

The sensors are configured for detecting and/or measuring data relating to user behavior (e.g., gestures, fitness activity, no users detected). In aspects, the sensor is a radar sensor that is configured to use Doppler-shift to detect and/or measure user behavior to generate Doppler-shift velocity data. Doppler-shift user behavior sensing may provide velocity information of the user by comparing the frequency shifts in the reflected signal from the reference transmitted signal. The radar sensor uses Doppler shift to emit a microwave signal (transmit signal) that reflects off an object and back to the sensor (returned signal). Based on the frequency of the returned signal, a change in the object's motion can be determined. In similar applications, current implementations of radar sensors in computing devices may provide velocity information of the the user behavior. In addition, radar sensors may differentiate static objects from moving objects, thereby reducing the occurrence of false negatives and/or positives in user behavior detection. However, this approach provides only Doppler shift velocity data, which is often noisy due to many ambient variations and does not provide user position in a given space. Furthermore, integrating this noisy signal to provide the position and proximity of the object (e.g., the user) from the device may inaccurate due to drifts and noise accumulation, leading to a possible inability to discern between user motion and other motion in a space (e.g., a rotating ceiling fan).

In another aspect, the sensor is an ultrasonic proximity sensor that is configured to detect and/or measure user behavior to generate proximity information (e.g., ultrasonic proximity data). The ultrasonic proximity sensor emits high frequency sound waves. The sound waves reflect off an object and back to the sensor, enabling ultrasonic proximity sensing via time-of-flight using cross-correlation of the emitted signal with the reflected signal. The position of the object can be analyzed based on the time it takes for the reflected signal to return to the sensor. While ultrasonic proximity sensing is a useful modality for detecting an object's position in a given space, current implementations cannot be used for several important use-cases and are often inaccurate. This is because in current implementations of ultrasonic proximity sensing, the cross-correlation of an emitted ultrasonic signal with a reflected ultrasonic signal provides proximity sensing but does not provide the velocity of the object. Additionally, there are many inaccuracies and inconsistencies in this approach due to multipath and reflection of static objects, which may create false negatives and false positives in user behavior detection, rendering this feature unreliable and inaccurate in current devices.

In aspects, an ultrasonic proximity sensor may be configured to use Doppler-shift to detect and/or measure user behavior to generate Doppler-shift velocity data. Doppler-shift user behavior sensing may provide velocity information of the user by comparing the frequency shifts in the reflected signal from the reference transmitted signal. The ultrasonic proximity sensor uses Doppler shift to emit an ultrasonic signal (transmit signal) that reflects off an object and back to the sensor (returned signal). Based on the frequency of the returned signal, a change in the object's motion can be determined. In addition, the ultrasonic proximity sensor may differentiate static objects from moving objects, thereby reducing the occurrence of false negatives and/or positives in user behavior detection.

The device data includes program instructions for one or more computer program modules (e.g., applications, an operating system) executable by the processor to provide functionality described herein. The term "module" refers to computer program logic (e.g., program instructions) used to provide the specified functionality. Thus, a module can be implemented in hardware, firmware, and/or software. The computer program modules in the device include a Fusion Manager module that represents functionality that receives, using data from the sensor(s), user behavior information; analyzes features of user behavior using a machine-learned model (ML model) to predict a user behavior; and then uses the predicted user behavior information to perform a function (e.g., open an application, go into sleep mode).

The device data also includes a ML model. The ML model may be a standard neural-network-based model with corresponding layers required for processing input features like fixed-side vectors, text embeddings, or variable length sequences. The ML model may be implemented as a convolutional neural network (CNN) or other machine-learning techniques. The ML model is trained to classify detected user behaviors and generate user behavior predictions.

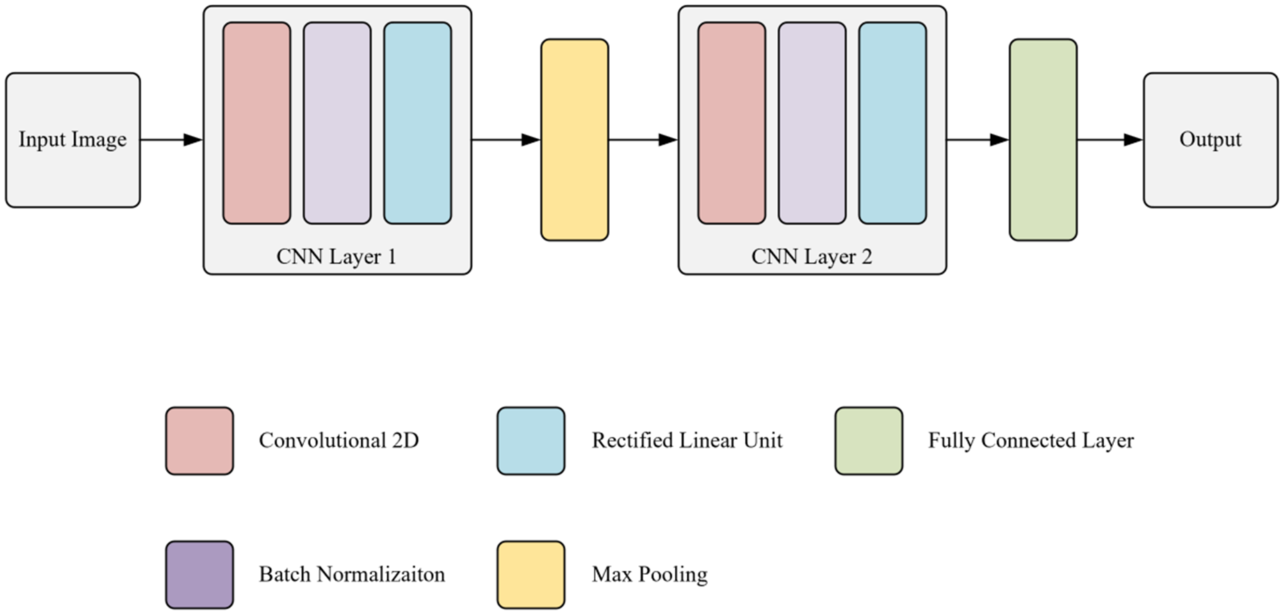

Figure 1

Figure 1 illustrates an aspect of a technique directed to the detection and classification of user behavior through the fusion of ultrasonic proximity data and Doppler-shift velocity data that may be performed by the Fusion Manager module to combine user position and velocity information. User behavior position is generated using an ultrasonic proximity sensor that detects user position within a space. User behavior velocity is generated using an ultrasonic proximity sensor or a radar sensor that detects user velocity within the space. The user behavior predictions generated by the Fusion Manager module enable the computing device to perform an action (e.g., open an application, power down) based on user behavior predictions. To provide the most accurate detection and sensing of various user behaviors, the technique combines the use of position sensing and velocity sensing.

In Figure 1, utilizing the ultrasonic proximity data and the Doppler-shift velocity data, a 2D input image that plots Doppler shift (velocity) versus proximity (position) from the computing device (e.g., distance of the user frame) is generated at each time instance (e.g., a scatter plot depicting a particular user behavior at that instance in time). This 2D image (Input Image) is fed into a first CNN layer (CNN Layer 1) that includes a 2D convolutional block, a batch normalization block, and a ReLU (Rectified Linear Unit) block. The output of the first CNN layer is fed to a Max Pooling layer that allows for faster computation speed by reducing the number of computations necessary on the network. The output of the Max Pooling layer is then provided as input to a second CNN layer (CNN Layer 2) that also includes a 2D convolutional block, a batch normalization block, and a ReLU block. The output of the second CNN layer is then fed to a fully connected layer to generate the final classification of various user activities as an output.

By generating continual 2D images over time, the Fusion Manager module of the computing device may be able to analyze user behavior to detect unique user behavior features (e.g., movement, exercise, location in a space). The Fusion Manager module may be equipped with pre-determined user behavior classifications such as various recognizable exercise movements (e.g., push-ups, jumping jacks, squats), or detecting no user movement (e.g., to tun on a power-saving mode). The CNN model may be trained through methods of machine learning to detect unique user behavior features and classify them into pre-designated activities to perform an action (e.g., open an application, go into power-saving mode).

Model training can be performed on a remote computing system. For example, to train the ML model, user behavior can be mimicked at a testing facility and the corresponding velocity vs. position 2D image can be collected into a dataset that can be used to train the ML model to recognize different features of user behavior. The remote computing system may send periodic model updates to the user computing device to continue classifying user behaviors and performing actions in real-time. After sufficient training, the ML model can be deployed to the CRM. Instead of, or in addition to model training on a remote computing system, the model training may be performed on the user computing device.

One application of the techniques described herein may include home health and fitness tracking. For example, assume that a user is beginning an exercise regimen in a room with a smart home controller device. When the user begins their exercise activity (e.g., push-ups, sit-ups, squats) the device will detect that a workout has begun and further detect the type of exercise the user is performing and open a fitness application. When the user has completed their exercise, the device may detect an input from the user to "End the workout" or no longer detect exercise activity and close the fitness application. In another application of the techniques described herein may include enabling a power saving mode of a computing device. For example, assume that a digital home assistant device is in a vacant space with no user activity detected; the device would power down or enter a sleep mode to conserve power until a new user activity is detected.

Throughout this disclosure, examples are described where a computing system (e.g., the computing device) may analyze information (e.g., user behavior information) associated with a user, for example, a fitness movement such as jumping jacks. Further to the descriptions above, a user may be provided with controls allowing the user to make an election as to which systems, programs, and/or features described herein may access information about a user's behaviors, and if the user is sent content or communications from a server. Further, individual users may have constant control over what programs can or cannot do with the information. In addition, information collected may be pre-treated in one or more ways before it is transferred, stored, or otherwise used, so that personally identifiable information is removed. Thus, the user may have control over whether information is collected about the user and the user's device, and how such information, if collected, may be used by the computing device and/or a remote computing system.

References:

[1] Patent Publication: US20200160046A1. Systems and Method for Action Recognition Using Micro-Doppler Signatures and Recurrent Neural Networks. Priority Date: June 30, 2017.

[2] Fu, Biying. "Sensor Applications for Human Activity Recognition in Smart Environments." September 24, 2020. https://diglib.eg.org/handle/10.2312/2633019.

[3] Patent Publication: US20220180723A1. Doppler Radar System with Machine Learning Applications for Fall Prediction and Detection. Priority Date: December 9, 2020.

[4] Nirmal, Isura, Khamis, Abdelwahed, Hassan, Mahbub, Hu, Wen, and Zhu, Xiaoqing. "Deep Learning for Radio-based Human Sensing: Recent Advances and Future Directions." Institute of Electrical and Electronics Engineers. February 7, 2021. https://arxiv.org/abs/2010.12717.