October 2021

Classification of User Input using System Contextual Information for Grip Suppression

Katherine Kuan

Mark Chang

Steve Pfetsch

Classification of User Input using System Contextual Information for Grip Suppression

Abstract:

This publication describes techniques for classification of user input using system contextual information for grip suppression on a mobile device (e.g., smartphone). In an example technique, a classification threshold is determined based on contextual information related to a current state of the mobile device and a heatmap is used to determine spatial features (e.g., amplitude, shape, size) relating to a user input on a touch panel of the mobile device. Based on a combination of the classification threshold and the spatial features, the user input is classified as intentional or unintentional. Using the techniques, unintentional user input, for example, those resulting from the user's grip on the mobile device, may be filtered out while intentional user input is accepted as valid.

Keywords:

machine learning, grip, suppression, touch, capacitance, touch screen, touch panel, intentional, unintentional, accidental, application programming interface (API), edge, spatial, temporal, heuristic, algorithm

Background:

The increased demand for mobile devices with relatively large screens has prompted the design of mobile devices having touch panels with thin and narrow screen borders. As a result, user input on the touch panel caused from a user's grip on the device can often be misidentified as user input (e.g., taps, swipes) meant to control the device. To eliminate this problem, user input on the touch panel is often classified as intentional or unintentional, and filtered based on this classification. However, some input classification systems have overly low classification threshold values that may result in unintentional control of the device due to gripping the device. Other input classification systems have overly high classification threshold values, which cause degradation in zoom/rotate performance, or the blockage of user input gestures. In addition, inaccurate input classification can have side effects, for example, degraded responsiveness and increased latency at the edge of the display.

Description:

This publication describes techniques for classification of user input using system contextual information for grip suppression on a mobile device.

The mobile device includes a processor, an input/output device (e.g., a display), a sensor (e.g., a touch panel), and a computer-readable medium (CRM). Device data (*e.g.*, a machine-learned model (ML model), a grip suppression algorithm, an operating system) is stored on the CRM. The device data may further include instructions that, responsive to execution by the processor, cause the processor to perform the techniques described in this publication.

The ML model is trained to examine user input to determine model parameters that are used by the spatial classifier to classify subsequent user inputs that are used by the operating system of the computing device to control the function of the mobile device.

The grip suppression algorithm includes a machine learning based (ML-based) spatial classifier to predict whether a user input is intentional or unintentional, a temporal classifier to store and extract useful information from previous user inputs, and a threshold control unit to adjust the classification threshold for a user input based on contextual information which pertains to a state of the mobile device at the time of the user input.

In an aspect, a threshold control unit may determine a classification threshold based on contextual information provided by the processor and related to a current state of the mobile device. The contextual information may include screen orientation, home screen activation, keyboard activation, video playback information, and system settings. A heatmap may be determined from the touch panel and used to determine spatial features (e.g., amplitude, shape, size) relating to user input on the touch panel. Based on a combination of the classification threshold and the determined spatial features, user input on a touch panel of a mobile device may be classified as an intentional input or an unintentional input. User input classified as unintentional may be filtered out while user input classified as intentional is accepted as valid. In doing so, the techniques described in this document may provide for more accurate classification of user input for use in grip suppression.

Figure 1 (below) illustrates an example system architecture for classification of user input using system contextual information for grip suppression as described in this document. A sensor (e.g., mutual-capacitance sensor (MS), self-capacitance sensor (SS)) is used to generate a heatmap from the digitized capacitance of a user input on the touch panel. The heatmap is pre-processed to determine a heatmap in a region of interest (ROI) provided to a machine learning based (ML-based) spatial classifier. Spatial features are extracted from the digital capacitance, for example, amplitude, shape, and size of the user input on the touch panel. The spatial features are used in combination with model parameters to determine an intention score calculated by the ML-based spatial classifier. The intention score indicates the likelihood of the user input to be intentional, for example, a high intention score may indicate a high likelihood that the user input is intentional.

Similarly, a low intention score may indicate a low likelihood that the user input is intentional. The model parameters may be a set of decisions incorporating one or more extracted spatial feature to determine the likelihood that the user input is an intentional input. For example, it may be determined that user inputs identified to have the spatial feature of a higher amplitude are more likely to be an intentional user input. As a result, a model parameter may include the amplitude spatial feature and calculate higher intention scores for user inputs with higher amplitude values.

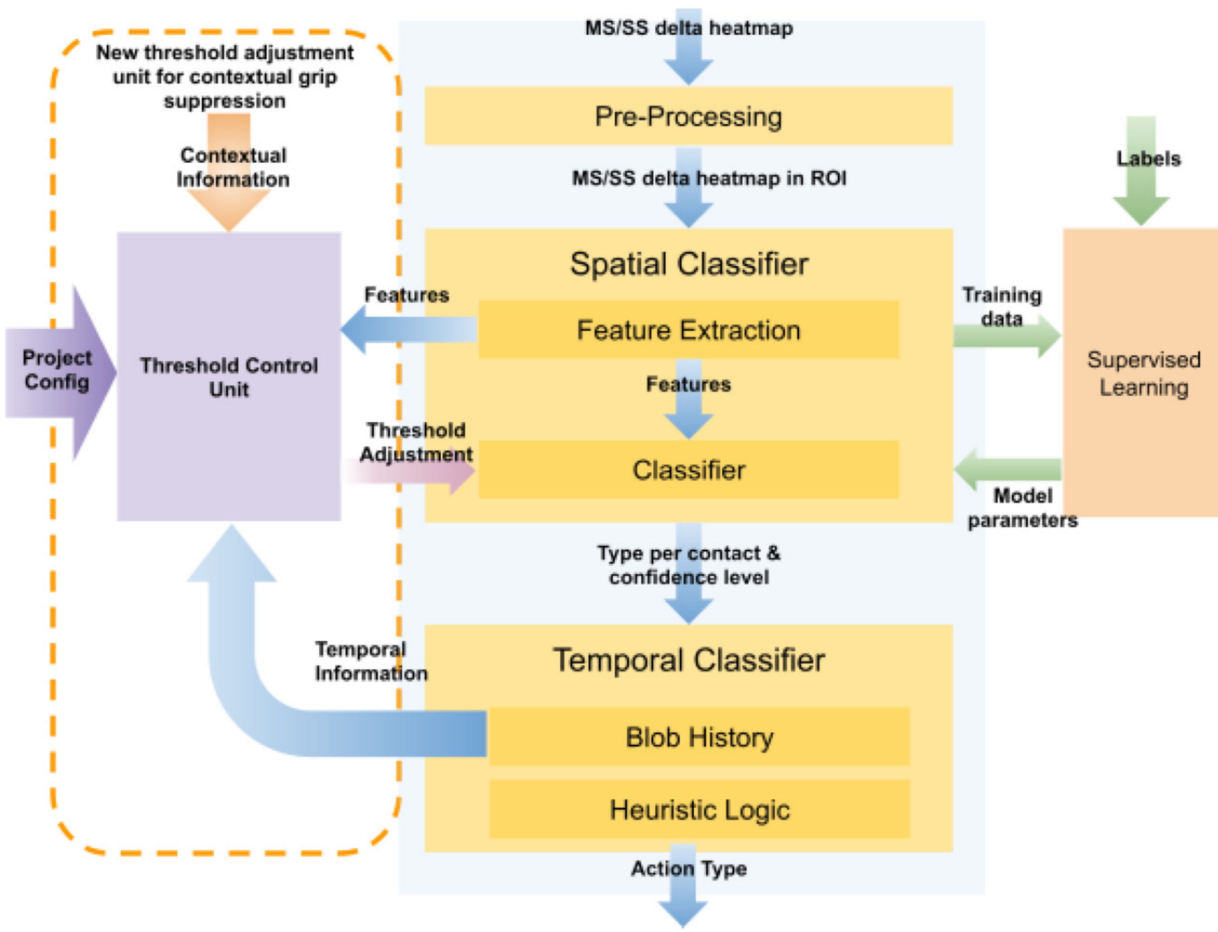

Figure 1

The model parameters are determined by the ML-based spatial classifier. The ML-based spatial classifier may be trained through supervised learning where training data with multiple user inputs each containing a set of extracted spatial features are class labeled. The ML-based spatial classifier may determine model parameters that best match each set of spatial features to its labeled intention score. Additionally, the ML-based spatial classifier may be trained during execution through supervised machine learning. For example, spatial features may be extracted from a heatmap associated with a user input. The ML-based spatial classifier may determine a predicted intention score for the user input, which is compared to a target intention score provided through supervised learning. The predicted intention score may be compared to the target intention score and the model parameters may be adjusted based on the comparison.

Once the model parameters are determined using the ML-based spatial classifier, the intention score indicating the likelihood that the user input is intentional is determined by incorporating the spatial features into the model parameters. The intention score determined by the spatial classifier is then used in combination with the classification threshold determined by the threshold control unit to classify the user input as intentional or unintentional.

The threshold control unit may be provided contextual information describing the mobile device through application programming interfaces (API). The contextual information may include screen orientation, home screen activation, keyboard activation, video playback information, and system settings usable as inputs to a grip suppression algorithm to determine a change in suppression strength. For example, the threshold control unit may be provided contextual information which indicates the orientation of the mobile device in a portrait configuration or a landscape configuration.

In an aspect, the mobile device may be determined to be oriented in a portrait configuration where the user is more likely to grip the mobile device at the long edge. As a result, the threshold control unit will increase the suppression strength at the gripping edge (e.g., the long edge) and decrease the suppression strength at the non-gripping edge (e.g., the short edge). Additionally, in the portrait configuration, user input at lower corners when viewed in the holding orientation is more likely to be caused from the user's grip on the device. Accordingly, the suppression strength at the lower corners will be increased while the suppression strength at the upper corner may be decreased or remain the same.

In another aspect, the contextual information may indicate that the mobile device is oriented in the landscape configuration where the short edge is the gripping edge and the long edge is the non-gripping edge. Additionally, the user is more likely to grip the corners of the mobile device when oriented in the landscape configuration. As a result, the threshold control unit may increase the suppression strength in the gripping edge (e.g., the short edge) and the corners (e.g., the upper corners and the lower corners), and decrease the suppression strength in the non-gripping edge (e.g., the long edge).

The threshold control unit may also be provided contextual information which indicates whether the home screen is active on the mobile device. When the home screen is active, the icons displayed are usually a short distance (e.g., at least 3-4 mm) from the edge of the touch panel. Accordingly, user input near the edges is more likely to be an unintentional input and the threshold control unit may increase the suppression strength at the gripping edge and the lower corners. In addition, the threshold control unit may decrease the suppression strength at the non-gripping edge and decrease or not change the suppression strength at the upper corners.

Alternatively, the contextual information may indicate that the home screen is active, an "allow home screen rotation" setting is enabled, and the mobile device is oriented in the landscape configuration. In this example, some icons may extend out of the bottom edge of the display. Accordingly, the threshold control unit may decrease the suppression strength at the lower non-gripping edge and decrease the suppression strength at the lower corners.

The contextual information provided to the threshold determination unit may also include gesture navigation information, for example, whether the mobile device is configured to use "3-button" navigation where the three buttons are located along the lower non-gripping short edge. If the contextual information indicates that "3-button" navigation is enabled on the mobile device, the threshold determination unit may decrease the suppression strength at the bottom non-gripping short edge and decrease or leave unchanged the suppression strength at the lower corners.

The threshold determination unit may be provided contextual information indicating that an on-screen graphical user interface (GUI) (e.g., a GUI keyboard) is active. When active, the GUI keyboard includes keys displayed close to the edge of the touch panel. As such, the touch panel must allow user input to be classified as intentional near the lower half of the mobile device. Accordingly, the threshold determination unit may increase the suppression strength at the upper part of the gripping edges and decrease the suppression strength at the lower part of the gripping edges.

Additionally, the contextual information provided to the threshold determination unit may include video playback information indicating whether a video is being displayed on the mobile device. When a video is being displayed, the user is more likely to tightly grip the corners of the mobile device, causing unintentional user input at the upper and lower corners. In response, the threshold determination unit may increase the suppression strength along the upper and lower corners. Further, the threshold determination unit may be provided information that indicates if video playback control icons are present along the non-gripping edges. If control elements are present along the non-gripping edges, the suppression strength at the non-gripping edges may remain unchanged, otherwise the suppression strength along the non-gripping edges may be increased.

The suppression strength changes can be weighted based on importance. For example, the threshold determination unit may determine that the device orientation is the most important contextual information. Accordingly, the suppression changes associated with device orientation may be given the highest weight.

The threshold determination unit may also be provided with temporal information relating to previous user inputs. The threshold determination unit may use the temporal information, the contextual information, and the spatial features to determine a classification threshold through one of two methods. The first method utilizes contextual information, blob position information (e.g., user input position information), and temporal information provided by a temporal classifier, including blob history, to determine a baseline decision threshold. The blob history contains information associated with previous user inputs, including extracted spatial features, intention score, and input classification for each of the previous user inputs. In one example of configuration parameters, the spatial features of the user input may be compared to the blob history to identify a set of previous user inputs with similar spatial features. The baseline decision threshold may be the threshold value that best classifies the set of previous user inputs with similar spatial features into their appropriate classification. For example, the previous user inputs with similar spatial features may be classified by the determined baseline decision threshold. The threshold determination unit may determine each of the previous user inputs classified incorrectly and calculate a least-squares summation of the difference between the intention value and the baseline decision threshold. The threshold determination unit may determine the baseline decision threshold that has the lowest least-squares summation.

Additionally, the configuration parameters may be determined to bias the baseline decision threshold to classify the user input as intentional or unintentional. In an aspect, the configuration parameters are determined based on performance tuning. Further, the configuration parameters may be associated with the touch sensitivity of the mobile device. For example, a high touch sensitivity may bias the baseline decision threshold to classify a user input as intentional.

The method may then adjust the determined baseline decision threshold based on the contextual information and the blob position information. The contextual information and blob position information can be used to add a scalar to the baseline decision threshold, modify the parameters used for calculating the baseline decision threshold, multiply a scalar by the baseline decision threshold, or set a maximum or minimum to the baseline decision threshold.

In an aspect, the contextual information and the blob position information are used to offset the baseline decision threshold through the addition of a scalar. For example, the blob position information may be used to determine the position of the user input within the touch panel. If the threshold determination unit determines the suppression strength at the position of the user input within the touch panel should be increased, a positive scalar will be added to the baseline decision threshold. Alternatively, if the threshold determination unit determines the suppression strength at the position of the user input within the touch panel should be decreased, a negative scalar will be added to the baseline decision threshold. The offset baseline decision threshold is then determined to be the classification threshold provided to the spatial classifier.

The second switching mode method determines configuration parameters based on a parameter table. The parameter table includes various parameter sets corresponding to different possible configurations of contextual information provided to the threshold determination unit. Based on the indication of the contextual information provided to the threshold determination unit, a specific parameter set is determined with specific configuration parameters. The spatial features are compared to the blob history to determine a classification threshold provided to the spatial classifier. In contrast to the first method, this method does not involve calculating, then adjusting, the baseline decision threshold.

The spatial classifier compares the intention score with the classification threshold. In an aspect, the spatial classifier may classify a user input as intentional when the intention score is greater than the classification threshold. Similarly, the spatial classifier may classify a user input as unintentional when the intention score is less than the classification threshold. Further, the spatial classifier may determine a confidence in the classification based on the difference between the intention score and the classification threshold.

The temporal classifier is provided the classification and the confidence or the user input to determine the intended action. In an aspect, the temporal classifier may combine subsequent user inputs to determine the intended action type using heuristic logic. Additionally, the temporal classifier may filter out user inputs classified as unintentional when determining the intended action type. Alternatively, the temporal classifier may filter out user input if it is classified as unintentional with at least a minimum confidence value.

The techniques for classification of user input using system contextual information for grip suppression on a mobile device also include a method. In a first step of the method, a heatmap is generated from the digitized capacitance of a user input on the touch panel and provided to a spatial classifier. In a second step of the method, the spatial classifier extracts features from the heatmap associated with the user input on the touch panel and provides them to a threshold control unit. In a third step of the method, a machine-learned model is applied to the spatial classifier to determine model parameters that are used to generate an intention score for a user input. In a fourth step of the method, the threshold control unit uses contextual information describing a current state of the mobile device and the extracted features to determine a classification threshold adjustment and provide it to the spatial classifier. In a fifth step, the intention score and the classification threshold adjustment are used by the spatial classifier to classify the user input on the touch panel as intentional or unintentional for use in grip suppression. After the spatial classifier, a temporal classifier is further used to both process the output of the spatial classifier, and to provide information to the control unit.

References:

[1] Patent Publication: US20160291731A1. Adaptive enclosure for a mobile computing device. Priority Date: December 24, 2013.

[2] Kuan, Katherine and Chang, Mark, "Grip suppression using a machine-learned technique," https://www.tdcommons.org/dpubs_series/4018/, (January 2021).

[3] Patent Publication: US20130176270A1. Object classification for touch panels. Priority Date: January 9, 2012.

[4] Patent Publication: CN106775405A. A kind of touch-screen false-touch prevention method of mobile terminal, device and mobile terminal. Priority Date: December 16, 2016.

[5] Matero, Juha and Colley, Ashley, "Identifying unintentional touches on handheld touch screen devices," https://dl.acm.org/doi/10.1145/2317956.2318031, (June 2012).

[6] Kim, Kee-Eung, "Hand grip pattern recognition for mobile user interfaces," Samsung Advanced Institute of Technology, https://www.aaai.org/Papers/AAAI/2006/AAAI06-296.pdf, (August 2, 2021).