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Face Touch Detection, Avoidance, and Related Training

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ABSTRACT

During times of widespread respiratory illnesses, users may put their own and others' health at risk by performing certain actions, e.g., touching their face when handling shared objects or when in shared environments; going to the restroom and not washing their hands thoroughly; returning home after visiting public or shared environments and touching other objects and/or their face before washing hands; etc.

This disclosure describes techniques that enable users to anticipate and detect face touch events as well as remind the user of recommended hygienic actions to help stop the spread of disease, e.g., the washing of hands. After a sufficient number of reminders (delivered, e.g., via buzzing, haptic-alerts, etc.), users may learn to anticipate the reminders and modify their behavior such that, over time, the dependency on device-generated reminders is reduced or eliminated.

KEYWORDS

- Public health
- Epidemiology
- Contact tracing
- Face touching
- Gesture recognition
- Smart home sensor
- Motion sensing radar
- Internet-of-things (IoT)

BACKGROUND

During times of widespread respiratory illnesses, users may put their own and others' health at risk by performing certain actions, e.g., touching their face when handling shared objects or when in shared environments; going to the restroom and not washing their hands thoroughly; returning home after visiting public or shared environments and touching other objects and/or their face before washing hands; etc.

During a pandemic situation such as Covid-19, a user who touches her face while in a public environment without having washed or sanitized their hands is at a greater risk of catching disease. The act of a user touching their face, nose, eyes, etc., gives an illness-causing agent such as a virus or bacteria an opportunity to infect the user. Although there are web-based tools that assist a user in face-touch avoidance, these work only when the user directly faces a camera.

DESCRIPTION

This disclosure describes techniques that enable users to anticipate and detect face-touch events as well as remind the user of recommended hygienic actions to help stop the spread of disease, e.g., the washing of hands. After a sufficient number of reminders (delivered, e.g., via buzzing, haptic-alerts, etc.), users learn to anticipate the reminders and retrain or monitor their behavior such that, over time, users decrease their dependency on device-generated reminders to the point of independence.

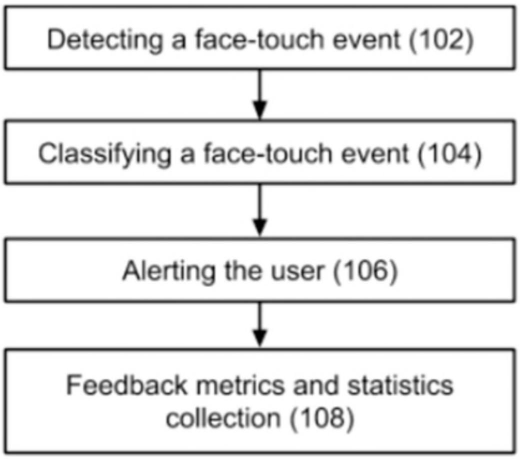

Fig. 1: Face-touch detection, avoidance, and retraining to prevent sickness

As illustrated in Fig.1, the disclosed techniques relate to the sensors used for detecting face-touching; the detection of face-touching events (102); the classification of such events (104); alerting mechanisms (106); and provision of feedback metrics and the collection of statistics (108); etc.

Sensors (or data) used to detect face-touching

Mobile devices, wearables, tablets, smart-home or smart-car devices, smart speakers, etc. typically include sensors that, with user permission, can be used to detect activity, information, or events relating to a user's health and well-being; for instance, whether or not the user has touched their face, how often, over what time period, and after what activities does face touching typically occur.

Sensors that can be utilized (with specific user permission) to perform hand and wrist tracking or otherwise detect a face-touch event include the following:

- **Smartwatch** with inertial measurement unit (IMU) sensors such as accelerometer, gyroscope, magnetometer, etc., to detect position, orientation, velocity, for classification of lift and drop/set-down gestures of the wrist.
- **Muscle or twitch-sensitive bands** that users wear around their arms or near their elbows, to feel/detect the use of muscle fibers in this area, which can help detect movement of hands, arms, and wrist, and predict movement.
- **Cameras** positioned on or around the face, especially external cameras such as those from webcams, cameras in smart-home devices, cameras on smart TVs, etc.
- **Radar or sonar-like sensors**, such as those available on certain smartphones, that can detect the position and velocity of nearby objects.
- **Infrared sensors**, similar to those used in video games consoles, which can be used to track fine-grained movement of hands, arms, and other appendages of the body.
- **Microphones**, for detection of audio events like sneezing or coughing, or even pleasantries like, "Bless you" or "Gesundheit", following, for instance, a non-audible sneeze, or detect the sound of someone blowing their nose, etc.
- **Directional and omnidirectional microphones**, e.g., those present on IoT devices in addition to smartphone or laptop/desktop microphones.
- **Global and/or local positioning systems**, e.g., WiFi or cell-tower location data to help triangulate where a health-related event occurred.

Many of the sensors listed above can be used to directly obtain sensor data that can be used to aid in sickness prediction. For instance, having an optical (RGB) camera video stream sample can be used to detect a user's pulse-rate and to determine if it is elevated or not, via remote photoplethysmography (PPG). Smartwatches can also perform such detection using builtin pulse sensors. Motion-sensing radar sensors or audio-based sonar, when targeted at the chest, can also be used to determine pulse-rate. WiFi being body reflective, can also be used to measure heart rate, as the WiFi reflectivity pattern can be quite sensitive to subtle body movements like heart-beats. Body temperature can be detected by using optical cameras by checking for signs of perspiration or flushness of cheeks, etc. Microphones can detect audio symptoms such as sneezing, coughing, wheezing, sniffing (to detect a runny nose), etc. To robustly detect health abnormalities, a good baseline can be used to calibrate such sensors and devices, e.g., not only for a specific user, and if permitted, from a crowdsourced database.

Detecting a face-touch event

Reminders can be sent to users based on their current or immediate-past locations, determined, e.g., by global or local positioning systems, geo-fences, etc. For example, based on WiFi hotspot names, GPS locations, etc., obtained with user permission, an alert can be issued similar to the following: “You just arrived home. Be sure to wash your hands!” Similarly, with user permission, it can be detected using GPS and by the fact of usage of a map application by the user that the user visited, for example, a supermarket by vehicle. The user’s fast speed on a roadway can be detected as being followed by slow-walking away, then slow-walking back to the vehicle, e.g., the last known GPS position of the fast-moving object the user was just in. In such a scenario, alerts such as the following can be issued: “state law requires you to wear a mask inside a building” when leaving the car, and “be sure to sanitize your hands before touching the wheel and other car surfaces!” when the user gets back into the vehicle.

When the user returns home, these sensors can be used to determine whether the user has performed a hand sanitization. The user makes specific, recognizable motions when either attempting to grab hand sanitizer or when washing their hands, and typically stands in place, in a designated area, for a noticeable amount of time. Such gesture and position-specific factors can be used to determine if the user has performed a hand sanitization, and if not, provide a reminder.

Classifying a face-touch event

Data from sensors can be used in conjunction with machine learning and deep learning algorithms, e.g., convolutional neural networks (CNN) trained to detect image events that are relevant from a hygiene point of view, including a person actually touching their face (image), or data that suggests this has happened (velocity data of arm movements, based on smartwatch sensors, radar, etc., leading up to a face touch event). Machine-learning models are also useful for classifying audio events that may be relevant from a hygiene point of view, e.g., audio-based deep neural networks (DNN), where an audio stream, or a vector of audio features, is fed to a neural network at a sampling rate such as 50 ms.

Other DNNs and sensors can be used for classifying meta-data about the event, including voice identification (deep learning network output embedding/vector of who it classified as the speaker); whether a sneeze was heard from the owner of the smartphone that is doing the detection of face touch events or from someone else; speaker identification/discrimination of same versus other. Other audio features include the fundamental frequency (F0), to determine if the speaker was an adult male vs. female speaker, if the voice identity is inconclusive or unregistered.

A special case of classification may include events such as coughs, sneezes, and nose-blowing events, each of which is also somewhat speaker/identity specific, as each user has their own distinct pattern. When in proximity to the person detecting the event, it is also useful contact-tracing information, regardless of the user to whom the event of blowing nose, coughing, sneezing, etc. is attributed. The more events detected, the more likely an alert is issued to the user to wear their mask, wash their hands, practice social distancing, etc.

Alerting Mechanism

The user is alerted when it is detected that they have touched their face, such that they can train themselves to touch their face less often. The alert is issued in real-time, e.g., in the form of haptic feedback, such that the user is made immediately aware of a face-touching event. The haptic feedback can be provided to the user via a smartwatch, smart glasses, smartphone, or any wearable device equipped with a vibration motor and/or speakers.

With user permission, the user's face-touching action can even be anticipated and corresponding feedback can be provided. For example, a smartwatch can detect that a user is lifting their wrist and can vibrate in a soft manner during the initial part of the lift, becoming stronger as the wrist nears the face. These devices can also send simple alerts based on activity such as arriving at home. For example, the user's virtual assistant can alert the user as soon as he enters through a door to wash his hands.

Feedback metrics

At periodic intervals, e.g., once a week, the user can receive a digest or summary of their face-touching activities (or lack thereof) throughout the interval. This helps the user understand if they are getting better, worse, or staying the same at avoiding face-touching. It can also help them determine whether, where, and when they may have gotten sick, if they feel symptoms. Such information can later assist in contact tracing, if the user recalls whom they possibly were with at the onset of infection. With permission, individuals who were near the user at the onset of infection can be alerted. In other words, the disclosed feedback metrics enable the correlation of two events, one in which the user, say, shook hands with someone, and another, subsequent event, in which the user touched their face unconsciously.

The feedback metrics also indicate the regions of the user's face which are the most touched. Such areas can be indicated by a facial map, e.g., red areas for frequently touched areas, yellow for less-touched areas, green for areas that experienced no touching, etc. If there are sensitive or problem areas of the face for a particular infection, e.g., eyes or nose, then touching such areas can trigger a red coloration on the facial map quickly. This data can be overlaid with a benchmark of how often other people near the user or over a larger geographic region, in the user's culture, profession, etc., tend to touch their face and in the same places. In this manner, to train the user in avoiding face-touching, even if there is insufficient touch data to know whether the person is touching their face a lot in a certain area, a benchmark heatmap of face-touching trends can be shown.

Statistics and crowdsourced detection

With user permission, a version of the aforementioned metrics, after removal of identifiable information can be shared with health authorities to better understand contact tracing and disease-spread statistics. It is possible that certain patterns emerge, e.g., perhaps people tend to touch their face a lot when they go to a coffee shop and unconsciously see other people doing this while waiting in line for a long time to get their drinks; or perhaps people are less likely to touch their face while in a drive through fast food restaurant where they are not interacting with other patrons waiting in line. Health-related behavioral patterns, as and when they emerge, can be used by the authorities to educate the public; to develop and recommend best practices; to selectively help vulnerable regions or businesses; etc.

Another use case is to understand how to recommend sanitizing the face to users who come back from certain errands. For example, if users are found touching their eye or nose regions frequently after certain errands, a recommendation can be issued that that errand be followed not only by hand sanitization but also eye and nose cleaning. Data on face-touching can assist in designing better personal protective equipment, e.g., face mask and eye coverings, face shields, etc. This analysis can also be useful in determining whether the use of certain equipment, e.g., gloves, is better or worse for a pandemic, e.g., to answer questions relating to the practicability of sanitizing and keeping clean non-disposable gloves, or equipment that tends to accumulate more debris that stays longer, and therefore are a more likely spread target. Face-touching data across a substantial population can also reveal the efficacy of face masks when properly washed or disposed.

The detection that a user is wearing one or more of certain PPEs, e.g., gloves, face masks, etc., combined with their face-touch heatmap, contact-tracing data, and aggregate disease-spread statistics, can enable the discovery of patterns relevant to public health. For example, a pattern that emerges might be that face masks, when properly worn, lower the spread of diseases with high contagion rate (R0), but gloves do not (or vice-versa). Suitable techniques such as differential privacy can be used to remove identifiable information from data.

Statistical epidemiological data, as generated using the disclosed techniques, can be used in various ways. For example, a navigation application can direct users away from areas that are more likely to lead to infection. The navigation application can further tune directions such that the user is warned against stopping in certain areas for eating or for filling gas and to provide driving directions via highways or other roads that are relatively insensitive to the presence of disease. Walking directions can be optimized to avoid regions with higher likelihood of disease spread.

Users can also be provided with options to select routes to avoid certain regions. Public and global health organizations can use statistical epidemiological data, as obtained using the disclosed techniques, to conduct ground-zero style contact tracing; to investigate disease spread, e.g., to identify how/when/where a disease is spreading; to measure its velocity; to predict its trajectory; to issue early warnings to communities; etc. This information can also be shared with store owners to help them prepare, e.g., by distributing hand sanitizers; by establishing social distancing points; by adjusting their schedules; by preparing more for deliveries than walk-ins; by closing sit-down areas; etc.

Further to the descriptions above, a user is 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 activities, face touch actions, 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 is treated so that no personally identifiable information can be determined for the user, or a user’s geographic location is 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 has control over what information is obtained about the user, how that information is used, and what information is provided to the user.

CONCLUSION

This disclosure describes techniques that enable users to anticipate and detect face touch events as well as remind the user of recommended hygienic actions to help stop the spread of disease, e.g., the washing of hands. After a sufficient number of reminders (delivered, e.g., via buzzing, haptic-alerts, etc.), users may learn to anticipate the reminders and modify their behavior such that, over time, the dependency on device-generated reminders is reduced or eliminated.

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