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mmWave Radar Return for Characterization of Burned Skin

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Abstract:

This publication describes techniques and systems directed to classifying skin injury using a radar propagation technique to measure the health of tissue below the surface of the skin. The millimeter-wave (mmWave) frequency of the electromagnetic spectrum can be broadcast from an active sensor(s) (*e.g.*, transmitting antenna(s)) on a computing device towards the skin of a person. The mmWaves penetrate the skin and reflectively scatter differently for various tissues and burn types due to changes in dielectric properties. Sensor(s) (*e.g.*, receiving antenna(s)) on the computing device can sense the scattering of the mmWaves reflected by the skin and collect data for processing. The data can be processed using data models supported by machine learning algorithms to categorize an assessment of skin injury. The computing device can further assess skin injury through the use of passive sensors such as light sensors (*i.e.*, camera) or infrared (IR) sensors.

Keywords:

Computing device, smartphone, radar propagation, dielectric properties, electromagnetic waves, millimeter-wave, mmWave, machine learning (ML), radar manager, RF generator, user interface, reflected waves, 5G, electromagnetic cross-section, radar cross-section characterization, phase, magnitude, recurrent neural network (RNN), neural network, dense neural network, convolution neural network, skin model, skin phantoms, reflectometry, Rayleigh scattering, infrared images, visual spectrum images, burn severity, skin, first-degree burn, second-degree burn, third-degree burn

Background:

The severity of a burn can be hard to characterize optically because the surface of the burn is only part of the burn identification visible. Skin has a number of layers. The epidermis is the superficial layer of skin that provides a barrier to infection. Deeper than the epidermis is the papillary layer of the dermis with a loose network of connective tissue. Deeper than the papillary layer is the reticular layer of the dermis that includes dense irregular connective tissue device with densely packed collagen fibers to provide structure and elasticity. The deepest layer of skin is the hypodermis, and it is primarily fat storage for regulating body temperature. The degree of a burn corresponds with the deepest layer of skin injured. A first-degree burn has only damaged the epidermis. A superficial second-degree burn extends to the papillary layer of the dermis. A deep second-degree burn extends to the reticular layer of the dermis. A third-degree burn extends to the deepest layer, the hypodermis, and is the most severe burn.

Some of these burns present with similar clinical symptoms. However, the burn depth, which determines the severity of a burn, is different for each degree of burn. Within a burn, some areas may be different depths making the same burn have more than one degree of burn.

Burns of multiple types (including thermal burns, chemical burns, etc.), share the common characteristic that injured skin layers have different dielectric properties than healthy skin layers. For example, skin with a first-degree burn may have additional liquid present due to blistering on the skin's surface, but skin with a second-degree burn may be dehydrated with lower moisture content. The ability to assess below the surface of the skin to correctly identify a burn can help clinicians guide burn treatment and triage burn patients. In the optical spectrum, energy reflects off the skin's surface, (*e.g.*, a visual camera picture,) but in the millimeter-wave spectrum, the energy can penetrate through the surface layer and is capable of measuring dielectric change at depth.

Alternatively, people who are outdoors may want to know information about their skin in the sun to avoid sunburn and reduce their risk for skin cancer. Recognizing a sunburn visually often occurs after a preventable skin injury. If a person knows the state of their skin is compromised, they have an opportunity to avoid injury.

Description:

This publication describes techniques and systems directed to classifying skin injury using a radar propagation technique to measure the health of tissue below the surface of the skin. Each layer of skin has dielectric properties that scatter electromagnetic waves differently. Further, healthy skin layers have different dielectric properties than injured skin layers. The millimeter-wave (mmWave) frequency of the electromagnetic spectrum can be broadcast from active sensor(s) (*e.g.*, transmitting antenna(s)) on a computing device towards the skin. The mmWaves penetrate the skin and reflectively scatter differently for various skin conditions and burn types due to changes in dielectric properties. Sensor(s) (*e.g.*, receiving antenna(s)) on the computing device can sense the scattering of the mmWaves reflected by the skin and collect data for processing. The data can be processed using data models supported by machine learning algorithms to categorize an assessment of skin injury. The assessment of skin injury can be further informed by passive sensors such as light sensors or infrared (IR) sensors.

A computing device, such as a smartphone, includes a radar manager application. The computing device, having a wireless connection to an access point of a wireless network, performs operations under the direction of the radar manager application to generate predictions for skin injury using mmWaves. The operations include: communicating to an RF generator to generate a mmWave, detecting scattered mmWaves, processing scattered mmWaves, determining the severity of burn injury using data that includes a machine-learned model, and, in response, communicating the burn injury to a user interface so that the computing device displays burn injury information to the user of the computing device on a display. Additionally, the computing device may communicate to a user additional information such as what action to take.

Fig. 1, below, illustrates an example computing device and elements of the computing device that supports a radar manager application.

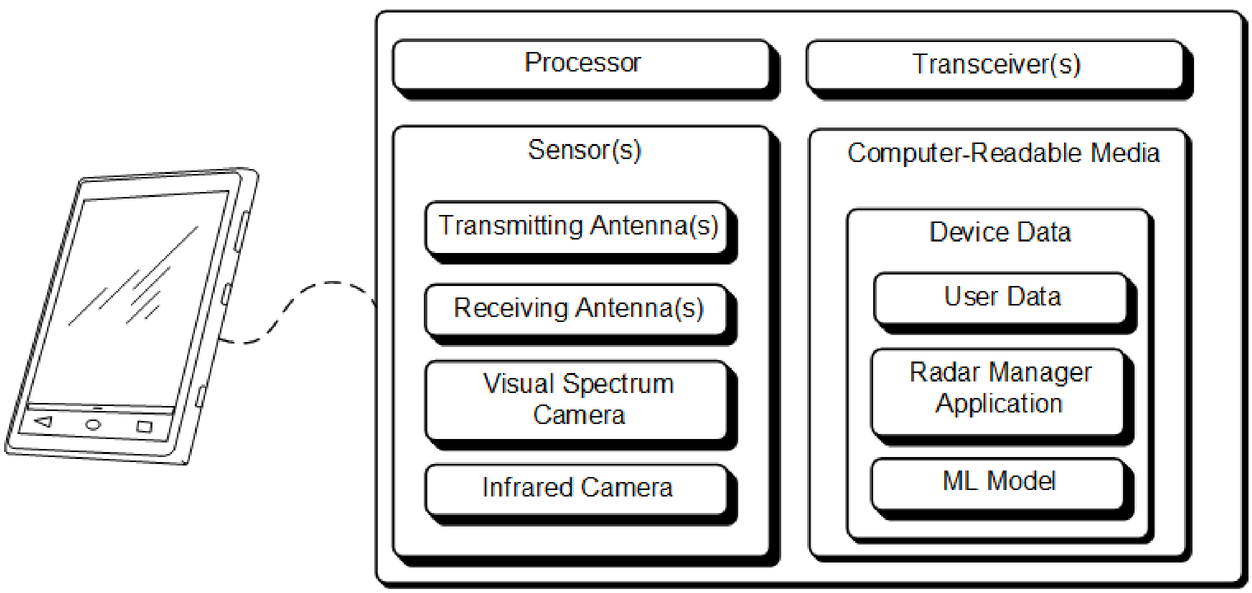

Figure 1

As illustrated, the computing device is a smartphone. However, other computing devices (*e.g.*, a tablet, a laptop computer, a wearable device, or the like) can also support the radar manager application described in this publication. The computing device includes a processor(s), transceiver(s) (*e.g.*, a 4G LTE transceiver, a 5G NR transceiver) for transmitting data to and receiving data from an access point of a wireless network, sensor(s) (*e.g.,* a transmitting antenna, a receiving antenna, a 5G transceiver, a 60 GHz transceiver) for broadcasting and collecting electromagnetic waves directed toward a target, and camera(s) (*e.g.*, visual spectrum and infrared). The sensor(s) may be the same transceiver(s) that communicate to the access point.

The computing device also includes a computer-readable medium (CRM) that includes device data. The device data includes user data, multimedia data, applications, a radar manager application, a machine-learned module, and/or an operating system of the computing device, which are executable by the processor(s) to enable classifying skin injury using mmWave radar technology on the computing device.

The device data includes executable instructions of a radar manager application that can be executed by the processor(s). The radar manager application represents functionality that generates electromagnetic waves to penetrate the surface of the skin and then processes reflected waves in order to identify skin damage below the surface of the skin. For example, electromagnetic waves from a 5G transceiver include waves in the millimeter spectrum at approximately 24 GHz-39 GHz. Electromagnetic waves from a 60 GHz transceiver include waves in the mmWave spectrum at approximately 59 GHz- 61 GHz. The 24 GHz-39 GHz waves can penetrate deeper into skin before they are reflected than the 60 GHz waves.

Additionally, each different frequencies (*e.g.*, 24 GHz-39 GHz, 60 GHz) can penetrate deeper depending on how much moisture is in the skin. The computing device can be directed toward the desired target skin. The user may view the burn area on the display of the computing device and then provide an input to confirm the desired target skin. The mmWaves are generated, transmitted from the antenna(s), and scattered as they pass through the skin, as illustrated in Figure 2. There will be changes to wave phase and wave magnitude due to the dielectric properties of the skin. The scattered mmWaves can be collected by a receiving antenna on the computing device. The change in phase and magnitude of the received mmWaves can be processed to determine how much scattering was produced by the target skin. The scattered electromagnetic wave data from targeted skin provides an electromagnetic cross-section that can be used to predict skin injury by a machine-learned model (ML model).

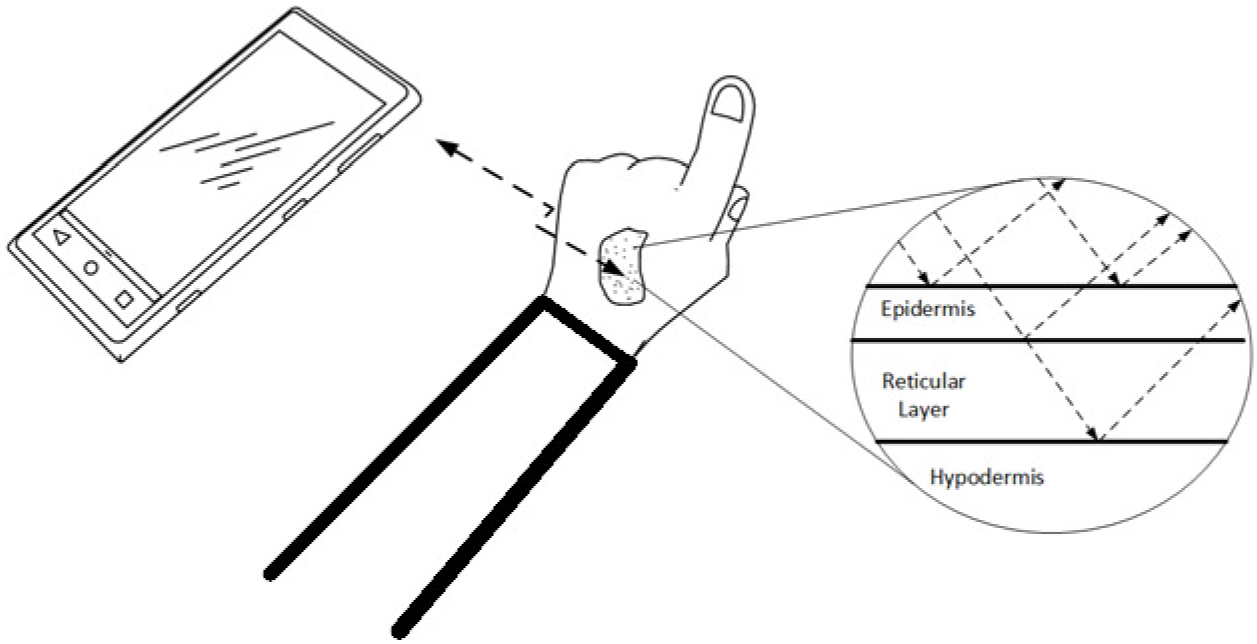

Figure 2

The CRM includes a machine-learned model (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 a support vector machine, a recurrent neural network (RNN), a convolutional neural network (CNN), a dense neural network (DNN), heuristics, or a combination thereof. Given the sizeable computational power that machine learning uses to train a model to analyze so many skin models, the model training may be performed on a cloud, server, or other capable computing device or system. The electromagnetic return of mmWaves can be categorized with corresponding burn severity to train a machine-learning model (*e.g.*, neural network). After sufficient training, the machine-learning model can be deployed to the CRM as a machine-learned model. Model training can be performed on a remote computing system. Instead of or in addition to, some or all of the model training can be performed on the computing device. The remote computing system can send periodic model updates to the computing device.

The ML model is trained to classify mmWave scatter that has passed through the skin to determine skin injury and generate predictions for the degree of skin burn that are used by a user of the computing device to treat a skin burn. In a first step, scattered electromagnetic wave data from physical skin models in a controlled environment can establish a baseline for radar cross-section characterization. During the first stages of machine learning training, the machine-learning model (*e.g.*, neural network) may be trained using mmWave reflectometry to examine radar return. Reflectometry uses different physical skin models (*e.g.*, skin phantoms) in a controlled environment (*e.g.*, an anechoic chamber) and subjects them to controlled mmWave scattering.

The circuitry supporting the mmWave reflectometry is illustrated in Figure 3. The radio frequency (RF) waves are generated, pass through a power divider, and then mmWaves are transmitted from the antenna(s) towards physical skin models. Multiple antennas provide more gain to the system. There will be changes in electromagnetic data phase and magnitude of the received mmWaves reflected from the physical skin models due to the amount of moisture located in each physical skin model layer. The received mmWaves are mixed with the transmitted mmWaves by a mixer. Received mmWaves will be relative to the local oscillators and the change in (*i.e.*, delta) from the power divided signal will have information in how much Rayleigh scattering was produced by the physical skin model. The data can be transmitted to a computer for further computations.

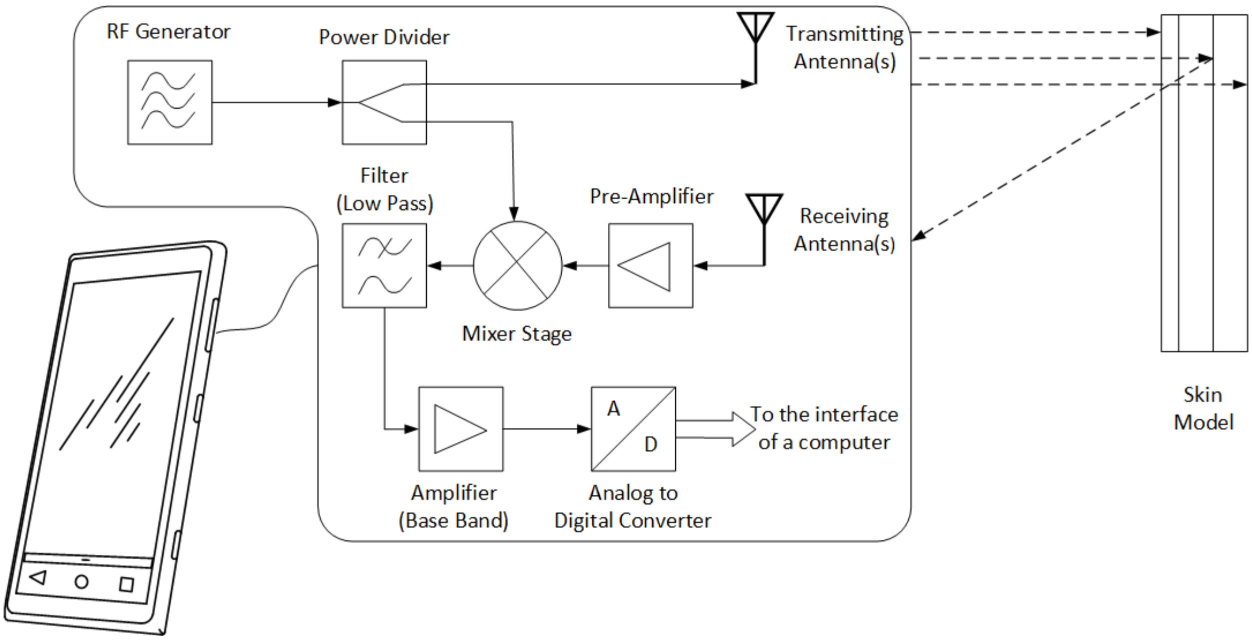

Figure 3

The properties of the physical skin models may be varied (*e.g.*, with different moisture content and dielectric content) to represent the diversity of healthy skin and injured skin to train the ML model. In particular, measuring the dielectric properties of the deeper levels of skin provides information about their moisture content. This data will be an analog to burned skin until biological models for burned skin can be used.

In a second step, scattered electromagnetic wave data from targeted skin is received. In a third step, a machine-learned model is applied to the scattered wave data from the physical skin models and the scattered wave data from targeted skin where the machine learning model is trained to generate a prediction of skin injury from the scattered wave data from the physical skin models and the scattered wave data from targeted skin. The prediction may be further informed by additional information sent from the computing device, including infrared and visual characteristics of the targeted skin. The ML model may compare pictures against vetted medical images of burn classifications. In a final step, a categorization of burn severity is obtained from the model. Using this data, the ML model can predict injury to the skin (*e.g.*, burn severity). The ML model may predict degrees of burn to the skin as a percentage (*e.g.*, 25% second-degree burn and 75% first-degree burn).

As the machine learning training, with some initial user input, creates a more-sophisticated model, periodic model updates are sent to each computing device, which allows the computing device to execute the model even if that computing device does not have the resources to update the model itself. The machine learning model can further train itself to the characteristics of injured skin as scattered wave data from biological models (*i.e.*, burned skin) is collected.

Figure 4 illustrates an example of how the OS of the computing device and/or applications installed on the computing device may use the machine-learned model to categorize burn severity.

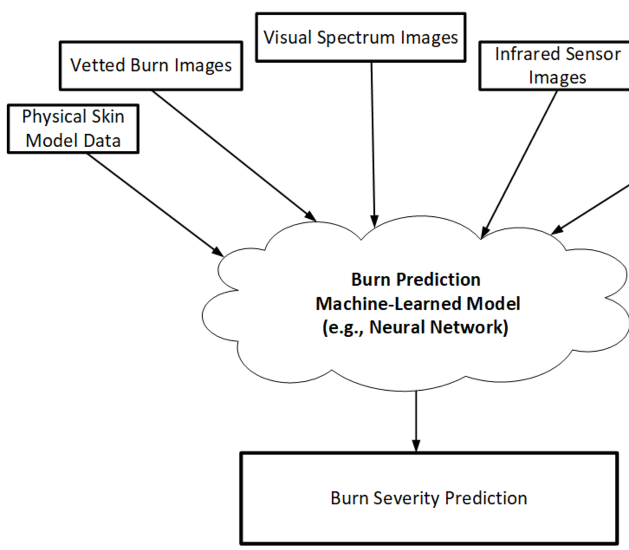

Figure 4

As illustrated in Figure 4, the OS of the computing device feeds several inputs to the machine-learned model. The computing device submits scattered electromagnetic wave data from targeted skin, visual spectrum images, and/or infrared spectrum images to the ML model. The ML model compares the inputs against known skin model data and vetted medical images of burns to determine a prediction for the severity of the burn.

Throughout this disclosure, examples are described where a computing system may analyze information (*e.g.*, radar, infrared, and visual sensor data) associated with a user, such as the skin features mentioned with respect to Figure 2. 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, and/or features described herein may enable collection of information (*e.g.*, information about the user, a user's preferences, a user's current location), and if the user is sent content or communications from a server. The computing system can be configured to only use the information after the computing system receives explicit permission from the user of the computing system to use the data. For example, in situations where the computing device analyzes sensor data for skin features to predict injury to the skin, individual users may be provided with an opportunity to provide input to control whether programs or features of the computing device can collect and make use of the data. 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. For example, before the computing device shares sensor data with another device (*e.g.*, to train a model executing at another device), the computing device may pre-treat the sensor data to ensure that any user-identifying information or device-identifying information embedded in the data is removed. Thus, the user may have control over whether the 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.

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