Smart UV: Track Your Sun Exposure

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ABSTRACT

The Ultraviolet (UV) radiation is one of the causes of skin cancer, skin aging and eye damage. Thousands of people are getting affected by skin cancer globally every year. UV radiation cannot be seen or felt, so it is important for people to be aware of the risks and regularly be reminded to take appropriate protective action. To overcome this problem, we present Smart UV: an ubiquitous application designed to dynamically warn users about their sun exposure and provide protection suggestions. Based on the estimated time the person is outdoor, the app tracks the user's sun exposure time in real-time. In order to detect if a person is outdoor, we implemented a classifier based on GPS sensor data. The resulting classifier performed very well in the tested environments, providing accurate estimation of UV exposure time. In addition, a separate app was designed to collect data for general-purpose indoor/outdoor classifiers and we finally present many ways to explore the app idea.

Categories and Subject Descriptors

H.1.2 [**User/Machine Systems**]: Miscellaneous; J.3 [**Life and Medical Sciences**]: Miscellaneous

General Terms

Human Factors, Algorithms, Verification

Keywords

ubiquitous computing, indoor outdoor classifier, sun exposure, UV index, machine learning, weka

1. INTRODUCTION

The UV Index is a measure of the intensity of the sun's ultraviolet radiation in the sun burning spectrum. As UV Index increases, the sun's rays can affect your skin, eyes and immune system. Therefore, you need to take more precautions to protect yourself from these harmful rays. According to World Health Organization (WHO), Ultraviolet (UV) radiation is a known cause of skin cancer, skin aging, eye damage, and may affect the immune system [1]. Approximately 130,000 skin cancer cases occur globally each year, substantially contributing to mortality rates in fair-skinned populations. An estimated 66,000 deaths occur annually from melanoma and other skin cancers. Worldwide some 12 to 15 million people become blind from cataracts annually, of which up to 2 million may be caused or enhanced by sun exposure according to WHO estimates. An obvious but very important way to limit your exposure to UV light is to avoid being outdoors in direct sunlight too long. This is particularly important between the hours of 10 am and 4 pm, when UV light is strongest. UV rays reach the ground all year, even on cloudy or hazy days, but the strength of UV rays can change based on the time of year and other factors. People in some areas may get sunburned when the weather is still cool or cloudy because they may not think about protecting themselves if it is not hot outside.

For people who are regularly exposed to the sun for long periods of time or who have sensitive skins, a more comprehensive strategy is required to minimize risks. This is because the sun is an UV radiation source that cannot be controlled like other workplace exposure hazards. As UV radiation can neither be seen nor felt, so it is important for people to be aware of the risks and regularly be reminded to take appropriate protective action. [2]

Smartphones and mobile applications are changing Americans' health communication landscape. Mobile phone interventions have improved preventive behaviors, including sunscreen use; however, nearly all employed simple, less interactive text messaging, rather than the latest smart phone technology. Smartphones can deliver engaging, personalized and real-time advice in using location and data services. This paper breaks away from established approaches to protect yourself from UV radiation, and explores an alternative way to check if you are indoor or outdoor and keep track of the amount of time to which you are exposed to sun. Smart UV can potentially generate tailored advice that should elevate self-efficacy expectations, improve response efficacy, and provide cues to sun protection practices. Finally, smartphones may reach high-risk populations that take relatively few precautions, such as males, young adults and children who are avid users of smart phones.

2. RELATED WORK

One of the most common and quickest ways to get information about UV Index is via Mobile application or online weather services. The low cost of featured smartphones and open availability of Google Play market has motivated various developers and mobile App enthusiasts to develop a variety of apps to help users learn about and protect themselves from the deleterious effect of the UV radiation. These including Sunsmart [3], sunZapp [4], and Sun Exposure [5].

These applications evaluate the sun exposure based on the user input information, such as their location, skin type, SPF of the sunscreen they are using, their clothes etc. The time involved in this process is relatively high and requires users to enter information about their sun exposure manually, which also requires users to open the applications frequently. Since they depend on the user engagement, these applications can yield unreliable results.

The increasing concern of UV radiation effects and the increment of ubiquitous computing has encouraged developers to collect data in a cost effective manner, without users entering any information on their smart phones, and warn who are exposed to these harmful rays frequently. There are some applications that dynamically provides updates about sun exposure, these being JUNE [6], SunSprite [7] and Sundroid [8]. However, these applications require the user to use wearable Bluetooth accessories or smartwatches, which are expensive and intrusive.

The closest related work is Sun Bath [23], which is a very recent work that performs ubiquitous monitoring of human sunlight exposure in urban environments. The application uses location, sun position, weather condition and the dimensions of surrounding buildings to estimate the user's sun exposure using a sophisticated ray tracing algorithm. The dimensions of the buildings are inferred through geometric analysis of satellite photos provided online. However, this implementation requires complex models and interaction with a server.

Smart UV is designed to be a robust, simple and dynamic application that warns users about their sun exposure. We designed and built a system from scratch to provide users with dynamic updates about the UV index based on their location and provide information about their exposure time. To the best of our understanding, incorporating these modules in any other existing application would require major changes in its core architecture.

3. METHODOLOGY

According World Health Organization (WHO) [9] and US Environmental Protection Agency (EPA) [10], people are more likely to get exposed to ultra violet radiation when they are outdoor. So, the plan is to design an app that tracks the amount of time the person has been outdoor as well as provide some suggestions and warnings based on estimated exposure time and the corresponding UV Index. For example, the app can provide protection advises and sunscreen reminders, such as sunburn time and high UV index alerts.

Thus, this project consists in developing an indoor/outdoor classifier and a background service that keeps track of the UV exposure time for each hour of the day along with the UV index. The project is mainly focused on the background structure. Since the time to develop this project was short, more sophisticated front-end features is proposed as future work.

3.1 Indoor/Outdoor Classifier

There are many approaches to estimate if the person is outdoor or indoor (or similar applications) using mobile applications. There is no dominant way to estimate the indoor/outdoor state so each approach has its own specific drawbacks. For example, [16],[18] and[15] explore GPS, WiFi scanning and other power-hungry sensors. [12][13][14] and [17] present alternative ways of using light sensor, magnetic field sensor, GSM signal strengths and Bluetooth beacons. These approaches implement complex models or they do not accomplish robust results.

Most of the articles claim that GPS is not practical because it is power-inefficient. However, none of them try to apply supervised learning on GPS status features and do not combine it with activity recognition to save battery consumption as Smart UV does.

The articles [12] and [13] state that light sensor is a very accurate feature to classify the indoor/outdoor state during day-time with simple threshold. Usually, the light sensor value is significantly higher when the person is outdoor compared to indoor. Since Smart UV is supposed to work during the day and the light sensor is lightweight in terms of battery consumption, we reuse their conclusions ([12][13]) and apply a light sensor classifier with a simple threshold of 2000 lux.

On the next sections, the chronological steps to develop the classifier are explained (all the related tests were done in a Nexus 5x phone powered with Android 6.0 Operating System).

3.1.1 Data Collection

The first step is to collect data for classification training. All the information contained in the GpsStatus object of Android API [19] is collected along with the accuracy and "first time to fix" values of the Location object ([20]). We also collected battery temperature, light sensor and GSM signal strength for future analysis.

Basically, GpsStatus contains information about the satellites used to estimate the phone's location. Usually, the sensor detects around 20 satellites. The main satellite information is the signal to noise ratio (SNR), that measures the ratio between the level of a desired signal and the level of background noise. Usually, the SNR is smaller in indoor places, because mechanical barriers usually degrades GPS signals.

Then, we developed an app, called "IO Collector", that collects data in the background and allow the user to record the current indoor/outdoor state by hitting the corresponding buttons. Figure 1 show the app interface.

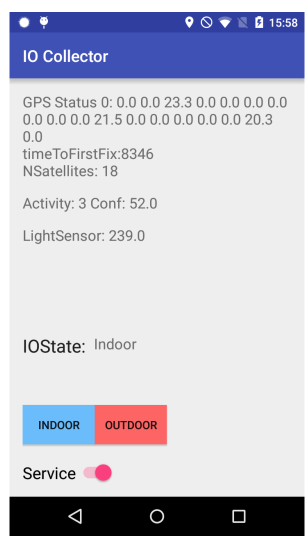


Figure 1: IO Collector

The table 3.1.1 show the main features extracted from GPS Data.

GPS Features	
$Accuracy$	Location accuracy [meters]
$FirstTimeToFix$	Time to get the first Location update
$AvgSNR$	Average of Satellites' SNR
$StdDevSNR$	Standard Deviation of Satellites' SNR
$Avg/StdDev(SNR)$	"Pseudo-Normalized SNR"
$\%(SNR < 10)$	(Count of satellites with $SNR < 10$)/(number of satellites)
$\%(10 \leq SNR < 20)$	(Count of satellites with $(10 \leq SNR < 20)$)/(number of satellites)
$\%(20 \leq SNR < 30)$	(Count of satellites with $(20 \leq SNR < 30)$)/(number of satellites)
$\%(SNR \geq 30)$	(Count of satellites with $(SNR \geq 30)$)/(number of satellites)
$\%(HasAlmanac)$	(Count of satellites that has Almanac)/(number of satellites)
$\%(UsedInFix)$	(Count of satellites used in the last fix)/(number of satellites)

Checking the SNR values for different environments, we observed that they range from 0 to around 45 units. So, we decided to group the satellites' SNR values in groups of 10 units.

The data collection phase lasted for almost a week, collecting GPS data every 5 seconds. The data was stored in a SQLite Database and exported for further analysis. The amount of data collected was not sufficient to split the data set into train and test, we used 10-fold cross-validation.

3.1.2 *Data Monitoring*

The second step was to do exploratory analysis on the collected data. With the help of Weka, an open source data mining software ([21]), some interesting patterns were found. Figure 2 shows the distribution of the collected instances for each feature in relation to the indoor/outdoor state.

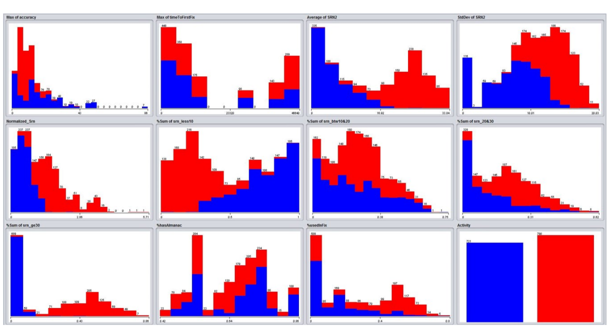


Figure 2: Histograms of various features

In the figure 2, the blue portion is when the user is indoor and the red portion is when the user is outdoor. It can be clearly inferred that some features, such as the one in the 3rd row and 2nd column, have a bad correlation and hence cannot be used as an input to the classification algorithm.

Having said that, we needed to find the best features for the algorithm to classify if the user is indoor or outdoor. In order to do so, we used some attribute evaluation techniques available in Weka like CorrelationAttributeEval, GainRatioAttributeEval, InfoGainAttributeEval and OneRAttributeEval feature evaluators. As an example, table 3.1.2 shows the feature rank for the CorrelationAttributeEval algorithm.

Table 1: Correlation Attribute Evaluator

Attribute	**Correlation**
$\%(SNR \geq 30)$	0.886
$AvgSNR$	0.874
$\%(SNR < 10)$	0.808
$Avg/StdDev(SNR)$	0.720
$\%(20 \leq SNR < 30)$	0.688
$StdDevSNR$	0.495
$\%(UsedInFix)$	0.487
$Accuracy$	0.319
$\%(HasAlmanac)$	0.178
$FirstTimeToFix$	0.170
$\%(10 \leq SNR < 20)$	0.134

The first 4 attributes were the same for all evaluators. They are the best predictors (inputs) for the classification algorithm to classify if the person is indoor or outdoor.

3.1.3 *Classifier*

As a next step of the methodology, the selected features were input to some machine learning classifiers in Weka. OneR, Logistic Regression, RandomForest and Naive Bayes were tested, because we were more familiar with these techniques and some of them are simple to implement. The results of these algorithms can be summarized in table 3.1.3.

Table 2: Classifier results

Algorithm	**Precision[%]**	**Recall[%]**
OneR	97.3	97.2
Logistic Regression	97.1	97.1
Naive Bayes	96.0	96.0
Random Forest	97.0	97.0

All classifiers presented good results. We decided to use Logistic Regression because it is simple to implement and it was more robust than OneR in practice. Table 3.1.3 show the resulting coefficients and the equation 1 shows the logistic function:

$$P(Indoor) = \frac{1}{1 + \exp(-(I + \sum_{n=1}^{4} c_n a_n))} \qquad (1)$$

In equation 1, c_n is the coefficient and a_n is the associated attribute value. The evaluation of the classifier is explained in section 4.

3.2 UV Exposure Tracker

Table 3: **Logistic Regression Result**

Attribute	Coefficient
$AvgSNR$	-1.19
$AvgSNR/StdDev(SNR)$	-1.18
$\%(SNR < 10)$	-27.78
$\%(SNR \geq 30)$	-6.03
$Intercept(I)$	31.68

In this module, the goal is to develop an app that track the time the user is outdoor and associate it with the corresponding UV index as well as show this information to the user. In addition, it is desirable to make it power-efficient and robust.

Basically, the structure of the app consists of a background service, that performs all the sensing, classification and UV tracking tasks; and an activity that handles the interaction with the user.

The following sections explain the architecture of the main service and the app interface respectively.

3.2.1 *Service Architecture*

Figure 3 illustrates the architecture of the background service.

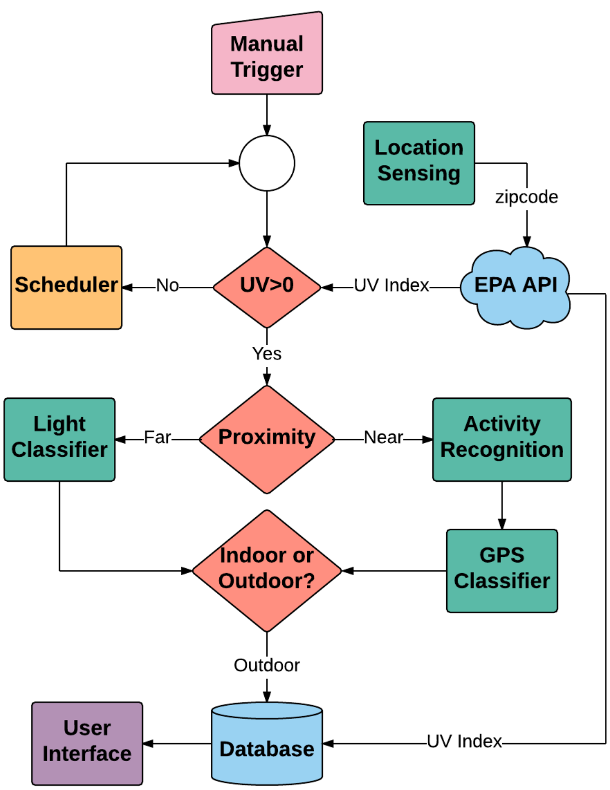


Figure 3: Smart UV app architecture

Firstly, it is important to state that the UV index information is fetched from the Envirofacts Data Service API ([11]) provided by EPA. As soon as the location sensing module (implemented with Geocoder and Google Location API [25]) receives an update, it requests the current UV index for that particular location.

Basically, the service can be triggered manually or automatically. The user has the ability to turn the service on or off. When it is on, the automatic scheduler is automatically set. The logic of the automatic scheduler relies on the fact that the app is supposed to work on times when the UV index is greater than zero, usually from 8am to 6pm. We call this period as "period of interest". Then, if the UV index is zero, the service reschedules itself to the beginning of the next period of interest. Although it is not shown in the figure 3, the service also schedules the time to turn itself off when it reaches the end of the period of interest as well as the next time to run.

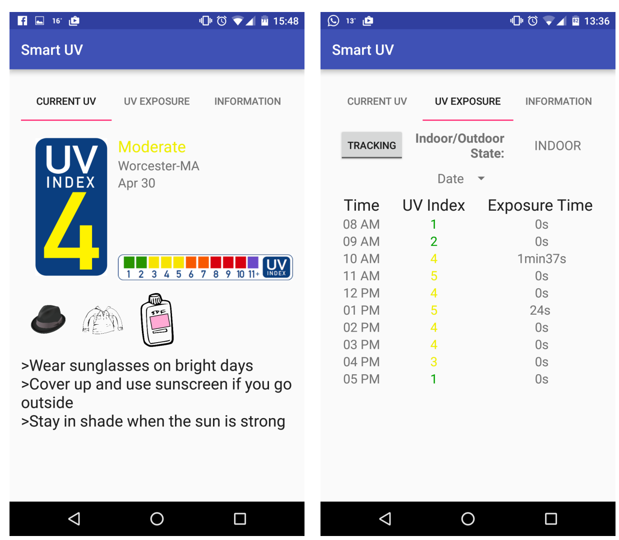
If the current UV index is greater than zero, it checks the proximity sensor to decide which classifier to use. If it detects "far", the light classifier is used. The light sensor is prioritized because of its power efficiency. When the proximity sensor detects "near", the light sensor is not available, than it switches to the GPS classifier.

The GPS classifier is indirectly controlled by the Activity Recognition Module. This module uses the Activity Recognition Google API ([25], that recognizes the user activity (still, on foot or in vehicle) mainly based on accelerometer sensor. The service does not request GPS updates if it detects that the user is still for consecutive readings, avoiding wasteful GPS power-hungry sensing. If outdoor state is detected, it counts the exposure time, save in the database and broadcast the information to the user interface.

In terms of coding, the sensing tasks are divided by modules and it is designed to make it easy to add any additional module in the future.

3.2.2 *Interface*

Since the focus of this project was to develop the ubiquitous background portion of the app, a simple interface was implemented. The figure 3.2.2 shows the two main screens.



(a) Screen 1 (b) Screen 2

The first tab shows the current UV index, along with the risk level, date and location name. Depending on the risk level, the screen dynamically update with protection messages and images based on information got from EPA ([10] and WHO UV index guides ([9]).

The second tab shows the period of interest of the day along with the UV index and the estimated exposure time for each hour. The ”Tracking” button allow the user to manually turn the main service on or off. For debug purposes, the screen also shows the current estimated indoor/outdoor state. Although the ”Date” spinner is present, it is not used yet. More interface ideas are discussed in section 5.

4. EVALUATION

The idea is to identify if the classification algorithm is providing accurate results. In order to do so, we collected the ground truth data from the ”Io Collector” application presented in section 3.1.1. We walked around various indoor/outdoor places in the campus of Worcester Polytechnic Institute (WPI) and got the results from the GPS classifier with the light classifier disabled and plotted it against the ground truth data as shown in figure 4.

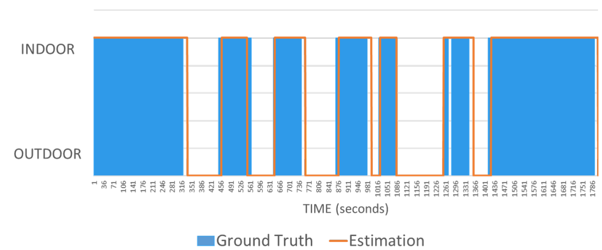


Figure 4: Evaluation

From the figure, it can be clearly seen that the classifier is almost as accurate as the ground truth data. There are some errors, most around the transitions moments. These errors are mostly due to the delay between the actual state transition and the sensing timestamp. In this experiment, the GPS status is collected every 15 seconds on average. Another major reason for the errors is that there are some places, such as buildings without walls, that cannot be clearly classified as indoor or outdoor, making the evaluation and the classification hard to be defined. The results can be summarized in the table 4.

Table 4: Evaluation results

Classification	Time[s]	Percentage[%]
Correct	1663	92.08
Incorrect	146	7.92
Total	1806	-

Given the limited time period for this academic project, we were not able to evaluate the algorithm under different environments neither for longer periods. Evaluating the same can be done as a part of future work.

5. FUTURE WORK

Smart UV is a promising and practical approach for providing real-time suggestions and warnings for people with sensitive skin and who are frequently exposed to sun, via smartphones. However, a number of limitations in the study must be overcome before Smart UV becomes ready for widespread usage.

Some of these work that needs to be still developed for widespread usage is as follows.

5.1 Technical Improvements

Besides some obvious improvements such as bug fixes and code optimization, some aspects need to be reviewed or enhanced. More data should be collected for classification and evaluation under different environments. In terms of evaluation, the data collection model including all sensor modules should be tested against the GPS-only version, the app should be tested in real-life situations and explore more ways to evaluate the app performance such as battery-consumption analysis.

5.2 Short-Term

Smart UV already provides good basement to implement many additional features. In a short-term future it is possible to add some visuals of daily UV index and sun exposure history. For example, Figure 5, taken from [9], show an example of daily UV index information

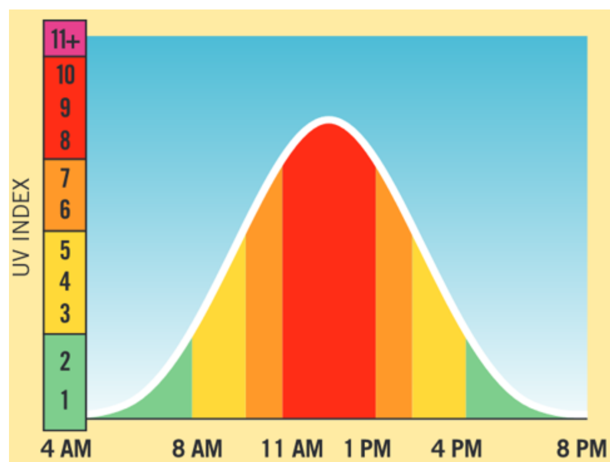


Figure 5: UV Visualization

In addition, the application could provide tailored alerts and notifications based on the accumulated sun exposure time and user skin type ([24]). The app can provide automatic alerts when the user may get sunburned and remind them to reapply the sunscreen. Figure 6, taken from [22] show one way to model the sunburn time for each skin type and UV index.

5.3 Long-Term

As a long term prospective, it is possible to aggregate more sensors to the indoor/outdoor classifier such as magnetic field sensors and GSM signal strength as explored in [12], cell tower and WiFi mapping ([13]) as well as Bluetooth ([14]). In addition, based on the collected data, temperature sensors can also be useful in situations when the temperature outside is very low or very high.

Other way to improve the application would be implement solar radiation models, as explored in [23], that estimate the user sun exposure based not only on location, but also on the sun’s position, weather condition and information from the surrounding buildings to infer if the person is in shade or not.

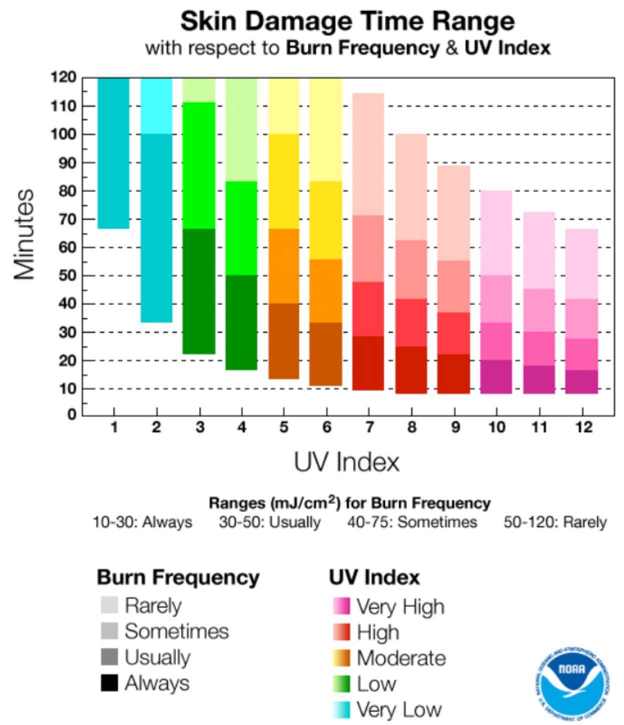


Figure 6: Sunburn time by skin type and UV Index

Interesting additional features can be added. Using the front-camera, the app could automatically detect if the user is wearing an hat or sunglasses to protect himself from harmful UV radiations and warn him if he is not wearing any protection. One more feature could be to automatically classify the skin type and identify malignant melanomas using camera.

6. CONCLUSIONS

In this project, we successfully developed an application that detects when the user is indoor or outdoor to estimate their UV exposure, and provide some precaution alerts. We also developed an efficient indoor/outdoor classifier using supervised machine learning algorithms based on GPS sensor data. To accomplish this, an additional general-purpose application, called "IO Collector" was developed to collect data for indoor/outdoor classifiers. Smart UV and IO Collector can be easily adapted to any indoor-outdoor detection application and provide accurate results.

The resulting GPS classifier was combined with other features such as light sensor, proximity sensor, activity recognition and automatic scheduling, resulting in a power-efficient and accurate data collection model. Along with the UV index information requested online, we display the estimated exposure time as well as general advises based on the current UV index.

Finally, we propose many ways to improve the application, showing that Smart UV is a promising app that deeply explore ubiquitous and mobile computing to help people, especially who has sensitive skin or is frequently exposed to sun, to protect themselves against the dangerous effects of UV radiation.

7. ACKNOWLEDGEMENTS

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