How much Light do you get?
Estimating Daily Light Exposure using Smartphones

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ABSTRACT
We present an approach to estimate a persons light exposure using smartphones. We used web-sourced weather reports combined with smartphone light sensor data, time of day, and indoor/outdoor information, to estimate illuminance around the user throughout a day. Since light dominates every human's circadian rhythm and influences the sleep-wake cycle, we developed a smartphone-based system that does not require additional sensors for illuminance estimation. To evaluate our approach, we conducted a free-living study with 12 users, each carrying a smartphone, a head-mounted light reference sensor, and a wrist-worn light sensing device for six consecutive days. Estimated light values were compared to the head-mounted reference, the wrist-worn device and a mean value estimate. Our results show that illuminance could be estimated at less than 20% error for all study participants, outperforming the wrist-worn device. In 9 out of 12 participants the estimation deviated less than 10% from the reference measurements.

Author Keywords
context inference, light intensity, light intake, circadian clock, circadian rhythm, mobile sensing

ACM Classification Keywords
I.5.m. Pattern Recognition: Miscellaneous

INTRODUCTION
Light entering through the eyes is the major cue of our human circadian rhythm and affecting sleep-wake cycle [2]. Human sleep is typically concentrated into a single continuous phase, which must be effective to maintain wakefulness during the day. Consequently, reduced sleep effectiveness was observed to affect performance, memory, alertness, gastrointestinal function, and others. In various studies, light exposure was found key in adjusting wake time: in the morning to advance the circadian phase and in evenings to postpone sleep, hence delay the circadian phase [5]. The exact illuminance necessary to modify the circadian clock is however widely discussed in literature, without clear conclusions. Recent investigations indicate that light stimuli may vary [3, 6], and categorical illumination levels, i.e. between dim lit indoors and bright sunny day outside could explain light exposure sufficiently. It appears therefore essential to assess light exposure continuously throughout the day to identify its timing and coarse level.

In free-living circadian phase studies, light exposure is measured using wrist-worn light sensors [4], or specialised, head-mounted sensors that record relevant light spectra directly at the eyes. The latter approach was frequently found impractical for continuous use during everyday life. Conversely, wrist-worn sensors can be occluded by cloths. Further alternatives included necklace devices that similarly may get hidden under garments. Measurement uncertainties resulting from ubiquitous devices require careful interpretation of the recorded light intensity data and hence illuminance estimation without continuous light measurement may become an alternative.

In this paper, we investigate an approach to estimate illuminance continuously by using smartphones only, without the need for additional sensors. We rely on robustly measurable user context features, including indoor/outdoor information, weather reports, time of the day, and smartphone light sensor measurements when available. These context features may provide sufficient information to estimate light exposure continuously. Based on the context features, we determine five illuminance categories using decision tree-based pattern classifiers. While it is clear, that our illuminance estimate cannot perfectly resemble a dedicated light intensity measurement close to the eyes, we show in this analysis that errors are below 20%, outperforming commonly used wrist-worn devices.

In particular, this paper provides the following contributions:

1. We detail our illuminance estimation approach that exploits user context features to select appropriate light intensity levels. Our implementation is based on pattern classifiers to categorise the illuminance situation, and subsequently estimate illuminance based on average light measurements in each illuminance category.

2. We evaluate our estimation approach in a 12-participant study. Each participant wore the smartphone as well as the wrist-worn sensor, and the head-worn reference for six consecutive days. We provide a comparative analyses of the estimation methods, and daily illuminance distribution.

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RELATED WORK

In this section we present related efforts in chronobiology and indoor/outdoor detection as required for this work.

Circadian rhythm has been constantly investigated in studies since the 1960's. Duffy and Wright [2] describe light as the dominant synchronizer in human circadian systems. Furthermore they state that the maximum clock shift observed in earlier studies was between -2 h and +3 h per day. Their work suggests that there are multiple severe health consequences if not being sufficiently entrained, such as impaired performance, alertness, as well as upset of gastrointernal function. Kantermann and Roenneberg [3] warn that light exposure during the night can damage DNA, which may lead to cancer. Individuals who live against the natural day/night rhythm, e.g. shift-workers, are particularly affected. Revell and Eastman [5] investigated how to minimise the influence of jet-lag on the circadian rhythm. They conclude that small circadian phase shifts are healthier than keeping the wrong rhythm. They state that phase delays are easier to achieve than phase advances as the period of the circadian clock in humans is usually slightly longer than 24 hours.

Choe et al. [1] reviewed existing technologies that help to measure and track sleeping behaviour. Moreover they conducted survey involving 230 participants to find the most important HCI factors that support healthy sleep behaviour. They found that users are not interested in carrying yet another device. In our approach, we use smartphones to estimate light intake, thus avoid additional devices.

Indoor/outdoor information is an important feature that affects illuminance estimation, as daytime outdoor light intensity is typically much larger than indoors. In [7] the authors aim at detecting indoor/outdoor information using a smartphone. They use accelerometer, light, proximity and magnetic field sensors as well as time of the day and cell tower RSSID to determine whether the user is outdoors, semi-outdoors (e.g. close to a building) or indoors. They deliberately abstain from using GPS due to it's power consumption. They achieve 88 % precision and recall when using a stateful detector (HMM) for indoor/outdoor detection. Our work relies on the user input for the indoor/outdoor information.

LIGHT ESTIMATION APPROACH

In this work we present an approach to estimate illuminance based on context data acquired from smartphone sensors and web-sourced weather reports. Hence, no additional sensors need to be worn or carried, except for the smartphone itself. Figure 1 shows a block schematic of the sensors used and the illuminance estimation process.

Feature extraction: smartphone sensor data was processed to extract features that could contribute to the light intensity estimation. Features included cloud coverage derived from web-sourced weather reports. We used the weather service from OpenWeatherMap (http://openweathermap.org) and used GPS coordinates to derive the most relevant report. This feature is particularly relevant to quantify actual outdoor light levels, i.e. during a sunny or cloudy day.
Light and proximity sensor information was recorded and interpreted such that during the sporadic moments when the phone was uncovered and an illuminance larger than zero lux was measured, e.g. when the phone was outside the pocket. During all uncovered phases the light sensor samples were captured. A light propagator block was used to resample the valid light samples such that a sample was considered until another valid measurement was found.
Time of the day was quantised into a 5-state sun level, where one level represented night time, and others were assigned to four time slices between sunrise and sunset. The sunrise and sunset times were also retrieved from the weather service.
Finally, indoor/outdoor information was used. For the present study an indoor/outdoor annotation provided by users through a lock screen widget. We nevertheless believe that it is well feasible to determine indoor/outdoor state using smartphone-integrated sensors only, e.g. see [7].
As light is a slowly changing parameter, measurements were recorded and converted to features every 30 s, except for GPS (on-demand sampling) and weather data (each four hours).

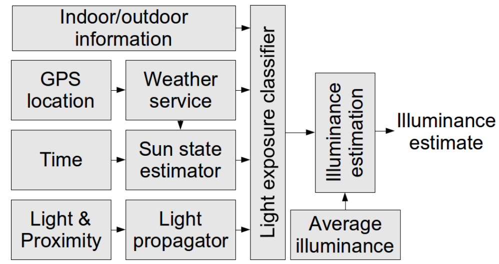

Figure 1. Architecture of our illuminance estimation approach. Features from several smartphone sensors were processed to obtain cloud coverage from weather reports, resampled light samples, sun state from time of the day, and indoor/outdoor information. Light exposure categories were classified from the features, and used for illuminance estimation.

Classification: features were fed to the light exposure classifier after applying a mean filter window of 5 minutes to all features. For classification, we used a decision tree, which was trained based on quantised illuminance levels of the reference measurement using 10-fold cross validation. We specified five illuminance categories shown in Table 1 according to the Illuminating Engineering Society table of standard illumination levels[1]. Illuminance estimation was performed by deriving the measurement average for each of the five illuminance categories from the reference measurements and assigned them to the estimation. In a practical application, the illumunace levels could be derived from measurements on the phone. In this work, processing was performed using MATLAB using the standard CART implementation. Maximum deviance reduction was used as a splitting criterion and impure nodes need to have at least 3 observations in order to be split. The illuminance estimation could be performed directly on a smartphone as it is computationally inexpensive.

[1]For more information see `http://ledlightingmanagement.com/led-lighting-management/content/standard-illumination-levels`

Table 1. **Illuminance categories used in this work. The categories were derived from IES table of standard illumination levels.**

Category	min [lux]	max [lux]	Description
1	0	119	Dark room
2	120	249	Dimmed room
3	250	999	Bright room
4	1000	4999	Cloudy
5	5000	∞	Sunny

STUDY METHODOLOGY

To evaluate the proposed methodology we conducted a free-living field study with 12 participants (5 female, 7 male between 18 and 28 years old). Each participant was given a Samsung Galaxy S III smartphone, a CamNtech MotionWatch 8, and a LightWatcher light sensor device mounted on a pair of glasses. The smartphones were handed out to ensure all participants use identical hardware. The LightWatcher served as our illuminance reference device. The sensor setup is shown in Figure 2. Participants carried the sensors for six consecutive days each. The recording duration was chosen since we expected that participant behaviour would differ between weekends and weekdays due to socially induced jet lag, hence light exposure would differ too. Participants were asked to recharge the smartphone at least once per day. From this study, we obtained a total of approximately 1700 hours of recorded data. One sample of data is written every 30 seconds. The recordings were not supervised nor were participants instructed to follow a script. Instead, participants were asked to follow their regular routines. Participants were compensated for their efforts with an Amazon voucher.

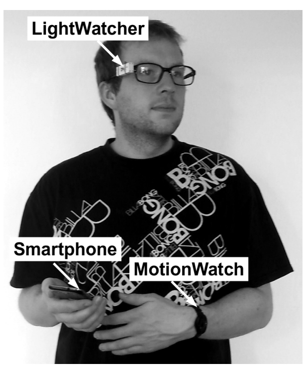

Figure 2. Study participant carrying a smartphone and wearing the glass-mounted LightWatcher and wrist-worn Motionwatch.

The smartphone was running the passive light estimation Android application as described in the previous section. The CamNtech MotionWatch 8 is a wrist-worn light and activity monitor, which is a popular measurement device in circadian rhythm studies [4]. We included the MotionWatch as a baseline measurement and for comparing measurements to our illuminance estimation.

As reference measurement, we used the LightWatcher device, which was developed in the EUCLOCK research project. For our study we mounted the LightWatcher on a pair of glasses, which were then worn by the study participants throughout the day and placed next to the bed during the night. Participants, who normally did not wear glasses were provided with a pair of dioptre-free glasses. The LightWatcher measures irradiance of each RGB channel separately. We converted the measured irradiance to luminous intensity using the standardised luminosity function normalised to a peak value at 555 nm.

Evaluation procedure

We derived the root-mean-square error (RMSe) between illuminance estimates e and light reference measurements r for all N measurements of each participant as

$$RMSe = \sqrt{\sum_{i=1}^{i=N} \frac{(e_i - r_i)^2}{N}}.$$

We further computed the $RMSe$ between the MotionWatch measurements and the reference as well as a mean probe and the reference. The mean probe was added to provide a baseline estimate for the illuminance estimation performance. For the mean probe each sample was set to the average of all illuminance reference measurements of a participant.

To assess the illuminance estimation error per day, we calculated the relative error Re per day per participant as:

$$Re = 100\% \cdot \frac{\sum_{i=1}^{i=N} e_i - r_i}{\sum_{i=1}^{i=N} r_i} \cdot \frac{N \cdot 5min \cdot 60 \frac{sec}{min}}{86400 \frac{sec}{day}}.$$

Finally, we analysed the light distribution over the day for our illuminance estimation and the reference measurements. For this analysis, we included all light measurements and estimations from one participant and assigned them to hourly bins. We then calculated the mean for each bin for the illuminance estimations and the reference measurements.

RESULTS

Root mean square error analysis

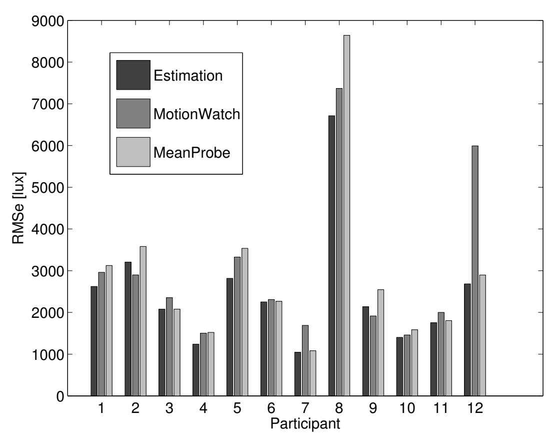

Figure 3. RMSe of our illuminance estimation, the MotionWatch measurements and the mean probe for each participant. In 10 of 12 participants, our estimation approach outperforms the MotionWatch device.

Figure 3 shows a comparison of the root-mean-square error (RMSe) between the reference measurements and our illuminance estimation, the MotionWatch, and a mean probe for the complete recordings of each participant. Our illuminance estimation achieves better results than the mean probe for all participants. The results further show that our illuminance estimation approach has a lower RMSe than the MotionWatch in 10 out of 12 participants. For Participant 2 and 9, the MotionWatch attains $\leq$10% lower error. In contrast, our illuminance estimate outperforms the MotionWatch in all other participants, by up to 100% RMSe (for Participant 12).

Relative error per day

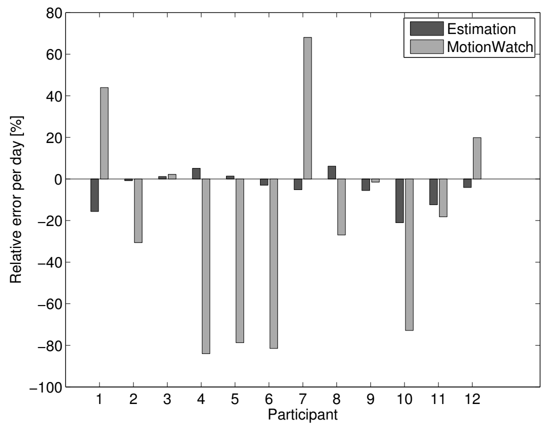

Figure 4. Relative error per day of our illuminance estimation approach and the MotionWatch, when comparing to the reference measurements.

Figure 4 shows the relative error observed per day for our illuminance estimation approach as well as the measurements taken with the MotionWatch. The figure shows that the maximal error of our estimation is -21%, hence underestimating the measured illuminance. In 9 out of 12 participants the estimation deviates less then 10% from the reference measurement. Furthermore, Figure 4 shows that our illuminance estimation approach outperforms the MotionWatch in 11 out of 12 participants. For Participant 9, indeed the MotionWatch estimates are lower, however level and difference are below 5% relative error.

Daily distribution of errors

We compared the light distribution within a day between our illuminance estimation and the LightWatcher measurements. Figure 5 shows that although our illuminance estimation incurs errors compared to the measured reference values, the daily light distribution curve is well represented by the estimated values. The hourly distribution also shows that the estimation error increases with the light values measured while in darker environments our estimation resembles the reference, typically with errors below 100 lux.

CONCLUSION AND FURTHER WORK

In this paper we introduced a novel approach to estimate light exposure in daily life using a smartphone and without additional sensors. For 75 % of participants we achieve a daily deviation of less than 10 % from the reference. When comparing the daily distribution errors our approach represents the reference measurements well. Simultaneously, our approach is more comfortable for the user as it only requires the user to carry a smartphone. In the future we intend to extend the dataset. Furthermore we would like to compare the decision tree model to a regression model.

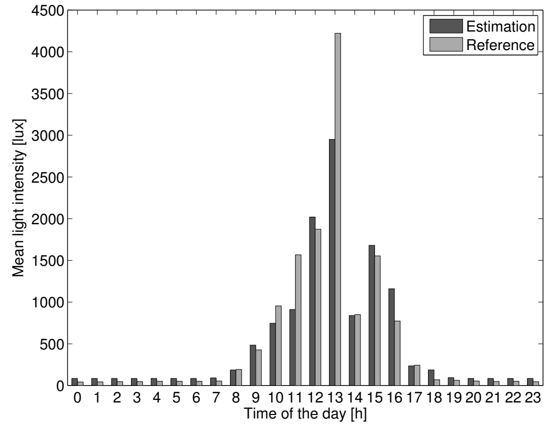

Figure 5. Illuminance distribution over the day, compared between the measured and estimated illuminance values for an example participant. As the distribution graph indicates, estimation error increases with the absolute light values. In darker environments, our estimation resembles the reference.

Acknowledgements

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