Potential of Large Area Photovoltaic Sheets as Indoor Interactive Surfaces

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Abstract
Human activity recognition in indoor environments is useful for comfortable and efficient living and working in smart homes and buildings. Energy harvesting technologies such as the photovoltaics could offer advantages for low-cost installation and maintenance, portability and energy savings. In this paper, we explore large area indoor photovoltaic (PV) sheets for both energy harvesting and gesture recognition and present early results to discuss and demonstrate its potential.

Author Keywords
PVs; Interactive; Tabletop; Gesture Recognition;

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CCS Concepts
•**Human-centered computing** → *Gestural input;*

Introduction
Today, we are part of a culture where technology plays an important role in almost everything. As technology is evolving, we have smaller and more powerful personal devices consuming lesser power. In recent years, with the introduction of the Internet of Things (IoT) and smart devices in the market, we witness a persistent integration of computing into our everyday life such as in homes and offices. The prohibiting factors in the adoption of these technologies are the associated cost of the device and its installation and maintenance and lack of human factors considerations. There are not many self-powered devices in households nowadays. Electricity is required to power most of them which are increasing our ecological footprint. However, indoor light energy can be captured and reused with photovoltaic (PV) cells. Such energy harvesting devices are enough to power small IoT devices [10, 19].

Interaction with IoT and smart devices with hand gesture recognition is an interesting proposition. Depth cameras and biomechanical sensors are currently used in indoors and personal devices for our comfort, efficient and safe living [17, 11]. Having smart homes and buildings recognise and understand the human body language would greatly

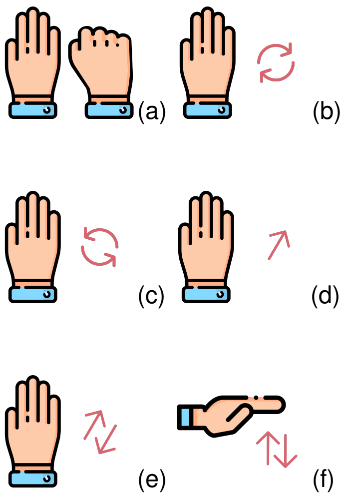

Figure 1: Example gestures, (a) Fist open/close, (b) clockwise hand rotation, (c) counterclockwise rotation, (d) swipe once, (e) swipe continuously, and (f) hand up/down

benefit the users. In this work, we are exploring the possibility of using a light energy harvester for hand gestures recognition for integration in smart homes and buildings. We specifically aim to examine whether a low cost and portable self-powered PV interactive tabletop is feasible and usable in indoor lighting such as with the existing lights in the ceiling.

An Example Use-case

Rose is sitting on the sofa in front of the TV. The coffee table in front of her has an integrated PV sheet for her hand gesture recognition, Figure 1. She makes a fist to hold the TV remote. Then she swipes to select the volume option. Lastly, she performs clockwise or counterclockwise hand motions to adjust the volume setting. She then makes a fist and with clockwise or counterclockwise hand motions selects the remote control of the smart light and changes its colour.

Related Work

Previous work has addressed the use of PV cells for energy harvesting in outdoor environments. For example, PV Glasses use semi-transparent organic PV cells as lenses to harvest light energy to power the ultra-low-power microelectronic circuit and displays [7]. PV materials have been combined with digital displays to present a prototype of ultra-low-power displays [5]. Amaravati et al. presented an ultra-low-power smart camera for gesture detection and powered it by ambient light harvested through PV cells [1]. Kartsch et al. presented a novel fully-flexible wearable EMG gesture recognition device and powered by an ultra-thin PV cell [6]. Yu et al. discussed a self-powered wearable tactile feedback system, powered by an organic PV module [21]. In contrast, we show both energy harvesting and gesture recognition in indoor settings using the PV cells like in PV-tiles [15], albeit using large-area PV sheets.

Light-based Interaction Technologies

Chakraborty et al. proposed a visible light-based gesture recognition system and used phototransistor (PT) as a light sensor for gesture detection [2]. Li et al. presented StarLight [9], an infrastructure-based sensing system used in a 3.6 m $\times$ 4.8 m office room, with customized 20 LED panels and 20 photodiodes. Zhang et al. explored visible light-based device-free localization (DFL) method, which has been widely developed for many applications including gesture recognition [4, 22].

PV Interactive Devices

Manabe et al. [14] proposed a touch-sensing technique using the partial shadowing of a small Si PV module. Li et al. presented LiSense which relies on an array of LEDs installed in the ceiling to reconstruct the entire human skeleton in 3D for gestures recognition [8]. Venkatnarayan et al. presented LiGest, an improvement over LiSense which can sense hand gestures from farther distance and is user agnostic, orientation agnostic and lighting condition agnostic [20]. Mahina-Diana Kaholokula presented GestureLite which detects hand gestures using Si PDs. These works do not discuss energy harvesting. Li et al. presented self-powered watches and glasses for finger gesture recognition using the ambient light using an array of PDs [10]. In contrast, we consider a single PV module with a large area with simpler electronics for large interactive surfaces with hand gesture sensing.

Ma et al. explored the transparent PV cells for hand gesture sensing and reported gesture recognition accuracy of 94.96% and 94.52% under 500 lux and 2600 lux, respectively [12]. Ma et al. presented a battery-free system which can perform gesture recognition using PV cells by analysing patterns of the photocurrent [13]. They reported that opaque PV cells show an accuracy of 97% and

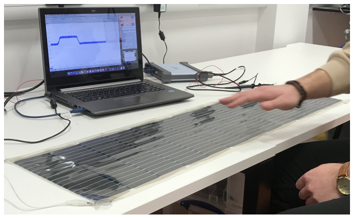

Figure 2: Prototype: The PV sheet and the recognition signals are shown.

Type	Bidirectional
Length (mm)	110
Voltage pr. meter (V)	56-60
Current (mA)	60-70
Power (mW pr.m)	ca. 2400
Cost (€ pr. m)^{d}	120 (110)

Table 1: infinityPV, Solar Tape General Specifications, 110mm wide bidirectional PV tape (> 4%). d: The quoted value is with lined adhesive on the backside.[1]

transparent PV cells can achieve accuracy of 94% whilst consuming 44% less power. In contrast, we present operation with indoor ambient light only and provide larger surfaces for the user to interact with.

Prototype

The current prototype consists of a large-area PV sheet [1], an energy harvesting circuit board and a single board microcomputer. The experimental setup is shown in Figure 2. The length and width of the PV sheet are 110 mm and 28 mm. It can generate up to 2.4 W/m with voltage and current 50-60 V and 60-70 mA, Table 1.

In the current prototype, both the harvesting energy and the recognition signals are sampled using the *two* electrodes of the PV sheet only. During energy harvesting, the PV module generates predominantly DC electricity as shown in Figure 3 due to stable indoor lighting. The recognition signal appears as AC modulation which is filtered by a series capacitor. The energy harvesting circuit board consists of a maximum power-point tracking (MPPT) module which continuously charges a rechargeable Lithium Polymer (LiPo) battery. The gesture recognition circuit board is connected to the load of the MPPT board. The recognition signal is connected to the recognition circuit board from the PV sheet.

Evaluation

We tested the prototype amongst the authors to create a set of six hand gestures to evaluate the prototype. We considered a set of potential use cases such as the one presented in the example applications. The gestures are shown in Figure 1. They are (a) fist open/close, circular swipe (b) clockwise and (c) counterclockwise, linear swipe (d) once and (e) continuously and (f) move hand up/down above the PV sheet as shown in Figure 1. The gestures were performed in a laboratory environment under standard workplace lighting condition, i.e. with multiple fluorescent lights in the ceiling giving a light power of about 800 lux. We performed the gestures over five seconds with a natural speed of movement of the hand.

The recognition signals corresponding to the six gestures in Figure 1 are shown in Figure 3. The signatures corresponding to each gesture is unique. The fist open/close gesture in Figure 3 (a) changes the DC level in the signal due to change in the size of the shadow from the hand. The signal shows flat top. The signal corresponding to the circular swipe gestures in Figure 3 (b) and (c) for the clockwise and counterclockwise motions are inverted in the time when compared with each other. The dynamic shadow pattern on the PV sheet involves the increasing/decreasing shadow from the arm. The signal shows a notch on the rising or falling edge. The signals corresponding to the linear swipe (d) once and (e) continuously are also unique. The signal for the continuous swipe gesture consists of multiple padded sequences of the signal corresponding to the signal swipe gesture. These signals have two sharp troughs without notches on the rising or falling edges. The signal corresponding to the (f) move hand up/down gesture changes due to the change in the intensity of shadow from the hand. It consists of rounded peaks and troughs without notches.

These unique signatures were consistently observed for different lighting conditions and position and orientation of the user and the PV sheet. The signals could be calibrated to different light conditions and users. A machine learning approach may be used for feature extraction [3] or train a classifier of Support Vector Machine (SVM) for pattern recognition. A cross-correlation algorithm could be used to extract patterns from the training data. A suitable algorithm

[1] infinityPV. https://infinitypv.com/products/opv/solar-tape

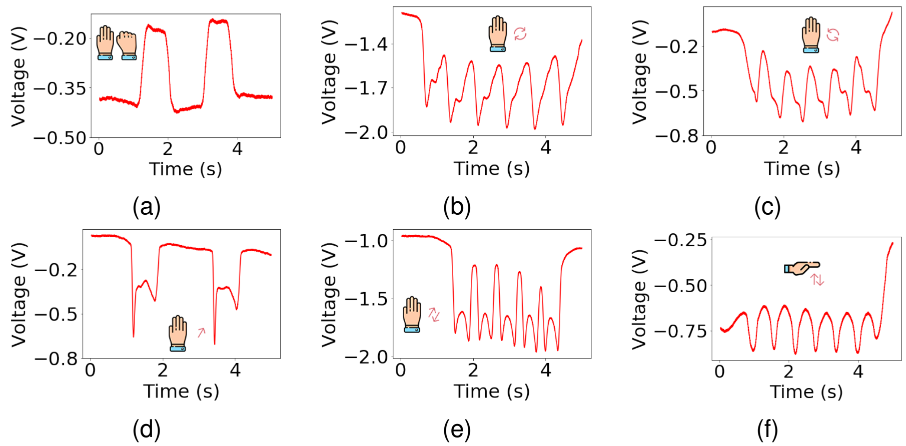

Figure 3: Gesture readings, (a) fist (open/close), (b) Clockwise motion, (c) Counterclockwise motion, (d) Singular swipe motion, (e) Continuous swipes motion, and (f) raise/lower hand motion.

could be selected based on complexity, execution time and energy cost.

Discussion

Artificial indoor lighting is required for reliable operation of the proposed device. This is particularly suitable in the workplace and overhead lighting environments. Inconsistent lighting in the operating environment poses a limitation. For example, despite artificial indoor lighting, the conditions will vary with the outdoor light conditions during the daytime through the transmitting surfaces like the windows and doors. More energy will be harvesting with the additional outdoor light. The base signal will increase. The gesture signals are generated by the shadows from the indoor light. The signal to noise ratio (SNR) will decrease due to light from outdoors. As a result, the performance of the system might deteriorate during the daytime. The SNR in the current prototype is very low without artificial indoor lights.

Unreliable indoor lighting could also be a limiting factor. Different kinds of light sources may introduce unpredictable noise in the gesture recognition signal. Dimming or switching off one or multiple light sources, flickering and light from a temporary external source such as a torch or car headlight could contribute to unreliable behaviour of the proposed system. The proposed device requires adequate light to be useful according to the use case scenarios. For example, the device might need low overhead lighting to be useful during watching movies in a dark room.

The large area of the PV sheet allows the device to be operated in different positions to the ceiling light. The recognition signal is independent of the position of the shadow on the sheet. Large gesture input surfaces could be created by connecting PV sheets in series and parallel electrical arrangements. The proposed device could recognise the same gestures regardless of the position and orientation of the user, PV sheet and the ceiling lights.

A self-powered device could harvest enough energy for intermittent use. To increase the usage time, low-power energy harvesting and micro-controllers are available. Different modules on these boards could be put into sleep mode to conserve energy. Gesture recognition using real-time energy would be challenging. Trickle charging a rechargeable battery or a super-capacitor would provide enough power on demand. The training to recognise gestures for users could be energy expensive. Low-energy algorithms could be implemented to reduce the energy footprint in gesture recognition. The proposed approach is promising as many self-powered devices have been developed, such as battery-less cellphones [18] and cameras [16].

The proposed approach could give a low-cost sensor and computation suitable for decentralized control of IoT devices. However, distributed and centralized computation may lead to trade-offs such as privacy. To address these concerns, certain level of local computation to access or control the device and its resources will be necessary.

Future Work

To demonstrate the effective working of the prototype, it would need to be evaluated with a group of users. A set of useful gestures could be established in a design workshop. The gesture recognition algorithm could be trained within minutes for each user. The gesture recognition performance could then be evaluated with different height, position and lighting conditions. In the future, the gesture recognition pipeline will need to consider the different speed and variability of gestures from the users. The prototype could be further developed to work with multiple hands and users under different use case scenarios. For deployment, the power harvesting and gesture recognition electronics could be implemented on a single board computer for real-time hand gesture recognition. A custom application with midair toggles, sliders and dial input features could be deployed with a select group of users.

Conclusion

With the advent of IoT based ubiquitous interfaces, having the smart buildings understand the human body language with a self-sustained and portable device would greatly benefit the users and make human-computer interactions more intuitive and effortless. We could use the indoor light in our houses for self-powered devices using large PV sheets. The energy harvested could be enough to power interfaces with intermittent use around the building. Self-powered, mobile and low-cost interactive surfaces could be made using large PV sheets. We explored a useful set of gestures with unique signatures and demonstrated with a prototype made using off-the-shelf components. Our current work shows that the potential of using large-area PV sheets as interactive surfaces in indoor lighting is promising.

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