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Gesture Recognition with Transparent Solar Cells: A Feasibility Study

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ABSTRACT

Transparent solar cell is an emerging solar energy harvesting technology that allows us to see through these cells. This revolutionary discovery is creating unique opportunities to turn any mobile device screen into solar energy harvester. In this paper, we consider the possibility of using such energy harvesting screens as a sensor to detect hand gestures. As different gestures impact the incident light on the screen in a different way, they are expected to create unique energy generation patterns for the transparent solar cell. Our goal is to recognize gestures by detecting these solar energy patterns. A key uncertainty we face with transparent solar cell is that, to provide transparency, they cannot harvest from the visible spectra, which may lead to weaker energy patterns for the gestures. To study gesture recognition feasibility of transparent solar cell, we develop a 1cmx1cm organic see-through solar cell which provides high level of content visibility when placed on mobile phone screen. We then use the output current of the organic cell as the source signal for gesture pattern recognition using machine learning. Experimental results demonstrate that we can detect five hand gestures with average accuracies of 95%. We also compare gesture recognition accuracies of our prototype organic cell with those obtained from a conventional ceramic opaque solar cell, which reveals that organic solar cell can recognize some of these gestures almost as good as the opaque cells.

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KEYWORDS

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1 INTRODUCTION

Researchers have recently discovered a way to build transparent or "see-through" solar cells [1, 2] from organic materials. These cells absorb and harvest energy from infrared and ultraviolet lights, but let the visible lights pass through so we can see through them like a clear glass. This phenomenal discovery in solar cell technology is set to create a multitude of new applications not dreamt of before. Integrating transparent solar cells into sunglasses [3], windows [4–6], and smartwatch screens [7] introduces energy harvesting capability to the devices, without impairing their original functionality. In the context of a mobile phone, Figure 1 demonstrates the see-through capability of a 1cmx1cm organic solar cell that we developed in our photovoltaic research laboratory.

Inspired by its potential use as energy harvesting screens of mobile devices, in this paper, we seek to use such screens as a natural light sensor to recognize hand gestures. In recent years, integrating gesture recognition to consumer electronic has raised much attention, as it is one of the most important ways for human to interact with anyone and anything [8, 9]. To achieve this, a wide range of modalities, such as RF signal (e.g., Wi-Fi) [10], sound wave [11], visible light [12], motion sensor [13], and image (e.g., camera) [14], have been explored and demonstrated. However, unlike solar cells that provide extra power, these systems actually dissipate energy from the device.

Although a recent work has demonstrated the potential of conventional opaque silicon-based solar cells for gesture recognition [15], it is not certain whether the same could be achieved with *transparent* cells. Transparency means that the absorption efficiency of the solar cell in the *visible light band* is significantly lower compared to opaque cells. The lower absorption rate results in weaker responsiveness to the visible light. Moreover, [15] differentiates only three gestures based on the number of times the user repeats a basic hand movement, which is basically recognition of one gesture but with different counts. This requires the user to remember the hand movement counts to ensure correct gesture is communicated. Thus, whether the transparent solar cells can be exploited to perform user-friendly gesture recognition remains unclear and unexplored.

In this paper, our goal is to investigate the gesture recognition feasibility of transparent solar cells. We achieved this by developing a transparent solar cell in our lab, using it to collect its energy (current) generation data for different hand gestures, and then detecting patterns using machine learning. Our findings suggest that transparent solar cells are

Figure 1: Demonstration of see-through effect of transparent solar cell. The 1cmx1cm organic solar cell prototype developed in our lab is placed on a iPhone 7 smartphone screen displaying the text "Hello Word".

indeed capable of detecting hand gestures. The contributions of this paper can be summarized as follows:

- We experimentally demonstrate gesture recognition feasibility of organic transparent solar cells. We show that five hand gestures can be recognized with average accuracy of 95% by training typical machine learning classification algorithms, such as Support Vector Machine (SVM) and K Nearest Neighbor (KNN). To the best of our knowledge, this is the first gesture recognition study involving transparent solar cell.
- Our analysis reveals that the most informative gesture recognizing features of solar cell voltage are very simple — the *maximum*, the *minimum*, and the *range* (*maximum* minus *minimum*). This suggests that gesture recognition for solar cells can be realized with minimal additional complexity and power consumption.
- We compare gesture recognition performance of organic transparent solar cell against that of conventional silicon-based opaque solar cell. Our experiments reveal that the organic solar cell can recognize some of these gestures almost as good as the opaque cell.

The rest of the paper is organized as follows. Section 2 presents the transparent solar cell prototype developed in our laboratory and used in our gesture recognition experiments. Performance evaluation of gesture recognition is presented in Section 3. We review related works in Section 4 before concluding the paper in Section 5.

2 TRANSPARENT SOLAR CELL PROTOTYPE

Solar cells, opaque or transparent, convert energy from the incident light into photocurrent based on the photovoltaic effect [16]. The photocurrent is the main signal to be used

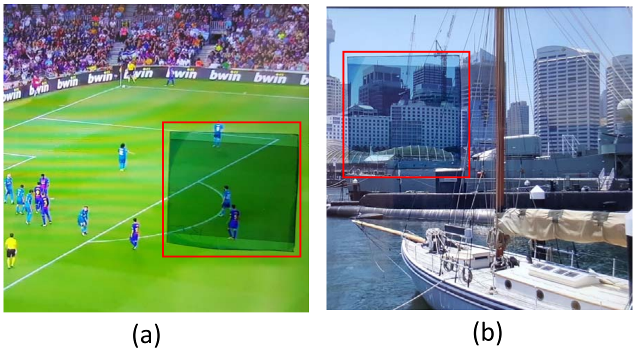


Figure 2: Effect of placing a transparent solar cell on a iPhone 7 smartphone screen that displays (a) a football match video, and (b) a still image.

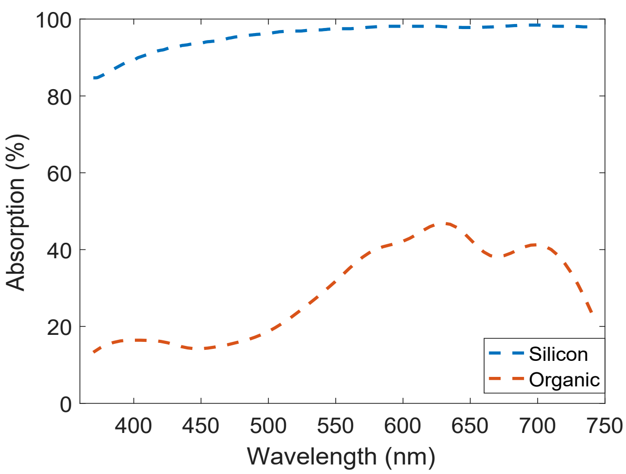


Figure 3: Absorption spectra of a conventional silicon solar cell (opaque) and our organic solar cell (transparent) within visible light band.

for gesture recognition. However, given a light condition, the amount of current is proportional to the absorption rate of the solar cell. Since transparent solar cells do not absorb a large fraction of the visible light, they are expected to produce less photocurrent hence weaker signals for gesture recognition.

To experimentally study gesture recognition capability of transparent solar cells, we have manufactured a 1cmx1cm organic solar cell with an average visual transmittance (AVT) of 35%[1]. Figure 1 and Figure 2 illustrate the see-through effect of the cell by placing it on a iPhone 7 smartphone screen while displaying different types of contents, i.e., text ("Hello World"), a soccer match video, and a landscape image. We

[1]Details of the material used as well as the manufacturing and characterization of the prototype are available from [4, 5].

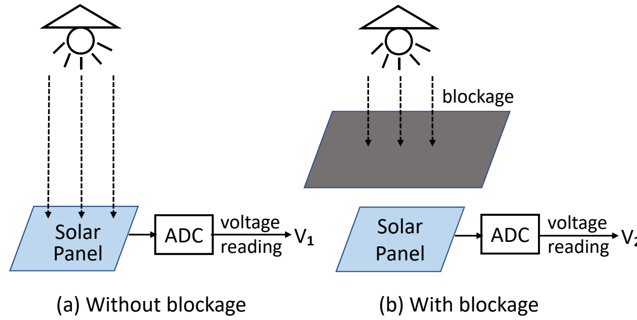


Figure 4: Illustration of SNR difference measurement.

can see that irrespective of the content of the screen, we can see through the cell and detect the displayed content.

Such transparency is obtained at the cost of losing some opportunities to absorb energy from visible light. Next, we study the effect of transparency on solar cell absorption efficiency. Within the visible light spectrum, i.e., wavelength ranging from 370 nm to 740nm, Figure 3 compares the light absorption rate of our transparent solar cell prototype against a conventional ceramic-based opaque cell. It can be observed that the opaque solar cell achieves nearly 100% absorption efficiency over the entire wavelength range, while the transparent cell absorbs only ~30%.

The lower absorption of visible light would result in weaker responsiveness to light change for the transparent solar cell compared to a conventional opaque cell. To demonstrate this, as shown in Figure 4, we utilize an analog-to-digital-converter (ADC) to measure the solar cell outputs when there is no blockage (refers to V_1) and when we cast a shadow over them (refers to V_2). Then, we calculate the signal-to-noise-ratio (SNR) differences between the blockage-free and blocked scenarios as $20\log_2(V_1/V_2)$ decibels. We find that the transparent and the opaque cells exhibit SNR differences of 21dB and 29dB, respectively, between the blocked and blockage-free scenarios. The focus of our study is to analyze the effect of this significantly weaker responsiveness to light change on the gesture recognition performance of transparent solar cells.

3 PERFORMANCE EVALUATION

The proposed framework for realizing dual functionality of both energy harvesting and gesture recognition using a transparent solar cell on a mobile device screen is illustrated in Figure 5. A mobile device integrated with a transparent solar panel is able to harvest energy from ambient light at anytime, where the harvested energy can be utilized as a power supply to extend battery life. When the user gives a gesture input, the generated photocurrent can also be acquired to identify user command using typical machine learning pipeline and

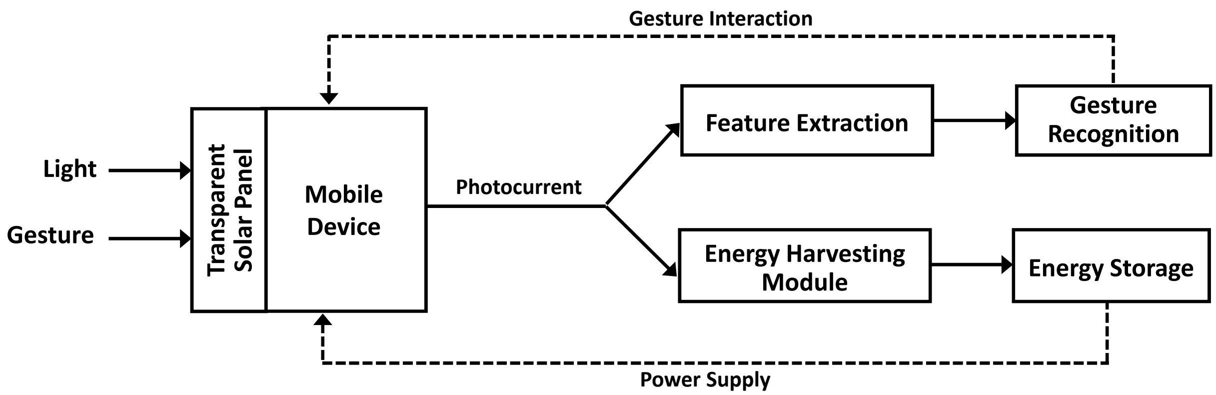
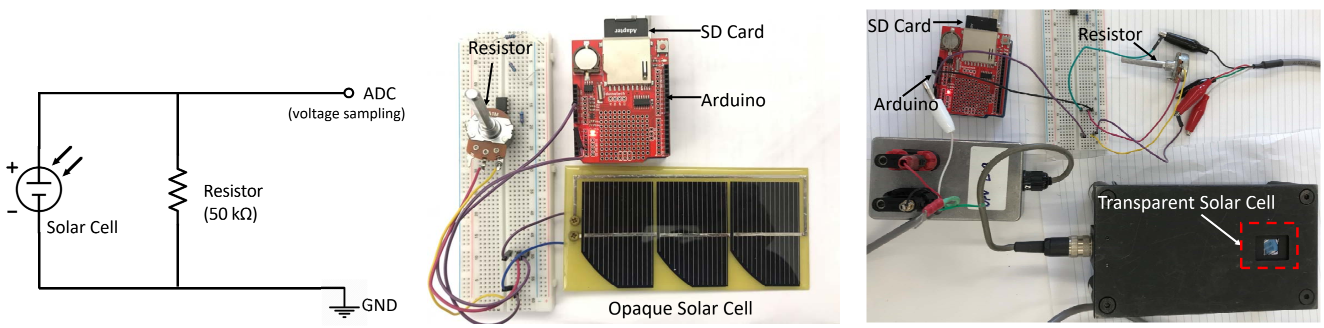


Figure 5: Proposed framework for realizing dual functionality of both energy harvesting and gesture recognition using a transparent solar cell on a mobile device screen.



(a) (b) (c)

Figure 6: (a) Circuit design for solar cell voltage data collection, (b) Experiment setup for opaque cell, and (c) Experiment setup for transparent cell.

Table 1: Solar cell parameters.

Solar cell	Material	Current density	PCE[1]	AVT	Size
Opaque	Silicon	$35mA/cm^2$	17%	-	$10*5cm$
Transparent	Organic	$13.82mA/cm^2$	6.1%	35%	$1*1cm$

[1] PCE refers to power conversion efficiency.

control the device, such as taking a picture or increasing music volume.

Next, we evaluate gesture recognition accuracies of our organic transparent solar cell and benchmark them against those obtained from a conventional ceramic opaque cell. Table 1 compares the parameters of these two solar cells. We first present the experimental design for data collection, then the methodology used for gesture recognition, and finally the results and their analyses.

3.1 Experiment Design and Data Collection

Figure 6(a) shows circuit design for data collection from the solar cells. A 50 kΩ resistor is cascaded to the solar cell to obtain the *voltage* across the resistor, which exhibits the same pattern with the *photoccurrent* generated by the solar cell. We implement the circuit design on an Arduino Uno platform where an analog-to-digital converter (ADC) samples the voltage at 500Hz and saves the data on a 4GB microSD. The opaque cell can be readily connected to the Arduino as shown in Figure 6(b). In contrast, the transparent solar cell prototype must be accessed from the specialized equipment as shown in Figure 6(c). For each solar cell, one subject is invited to perform five different hand gestures, as shown in Figure 7. Each gesture is repeated for a total of 100 times, but spread over two different sessions to avoid fatigue. The data were collected inside the lab with two light intensity levels, i.e., 500 *lux* for both opaque and transparent

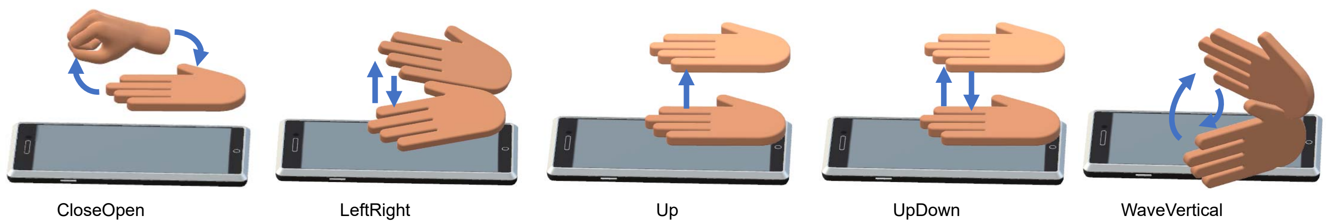


Figure 7: Illustrations of the 5 hand gestures conducted over the solar cells. *CloseOpen* refers to switching the hand state between *palm* and *fist*. *LeftRight, Up,* and *UpDown* represent palm movement in different directions. *WaveVertical* places the palm *vertically* over the solar cell and then swipes it.

Table 2: Features extracted for gesture recognition.

	Feature	Abbreviation	Description
Time-domain	Mean	MEAN	the central value of a window of samples.
	Standard deviation	STD	the square root of the variance.
	Maximum	MAX	the maximum value in a window of samples.
	Minimum	MIN	the minimum value in a window of samples.
	Range	RANGE	the difference between the maximum and the minimum values in a window of samples.
	Inter Quartile Range	IQR	the difference between the upper (third) quartile and the lower (first) quartile of the window of samples; also measures the dispersion of the signal samples over the window.
	Absolute Mean	AbsMean	average of absolute values.
	Coefficient of Variation	CV	ratio of standard deviation and mean times 100; measure of signal dispersion.
	Skewness	SKEW	measure of asymmetry of the probability distribution of the window of samples.
	Kurtosis	KURT	measure of peakedness of the probability distribution of the window of samples.
	Absolute Area	AbsArea	the area under the absolute values of the signal samples. It is the sum of absolute values of the signal samples over the window.
	Root Mean Square	RMS	the square root of the mean square of the samples over the window.
	Mean Absolute Deviation	MAD	the average of the absolute deviations.
	Quartiles: 1st Quartile 2nd Quartile 3rd Quartile	 Q1 Q2 Q3	measures the overall distribution of the signal samples over the window.
Frequency-domain	Frequency Domain Maximum	FDMax	the maximum value of the magnitude of FFT coefficients.
	Frequency Domain Mean	FDMean	the mean value of the magnitude of FFT coefficients (power spectrum mean).
	Dominant Frequency	Dominant	the frequency with maximum magnitude after FFT.
	Dominant Frequency Ratio	DomFreqRatio	it is calculated as the ratio of highest magnitude FFT coefficient to sum of magnitude of all FFT coefficients.
	Frequency Domain Energy	FDEnergy	it is a measure of total energy in all frequencies. It is calculated as the sum of the squared discrete FFT component magnitudes.
	Frequency Domain Entropy	FDEntropy	it captures the inpurity in the measured data. It is calculated as the information entropy of the normalized values of FFT coefficient magnitude.

solar cells and 2600 *lux* for the transparent solar cell only (using a lamp to increase light strength).

3.2 Gesture Recognition Methodology

The collected data contains time series of *voltage samples*. We use 1-sec windows with 50% overlap to split the time series into individual gesture *instances*, where each *instance* consists of 500 consecutive voltage samples. For each instance, we extract a set of 22 typical statistical features [17] as shown in Table 2. Therefore, each gesture *instance* is converted to a corresponding feature *vector* of 22 elements. To ensure a balanced dataset for unbiased training and classification, for

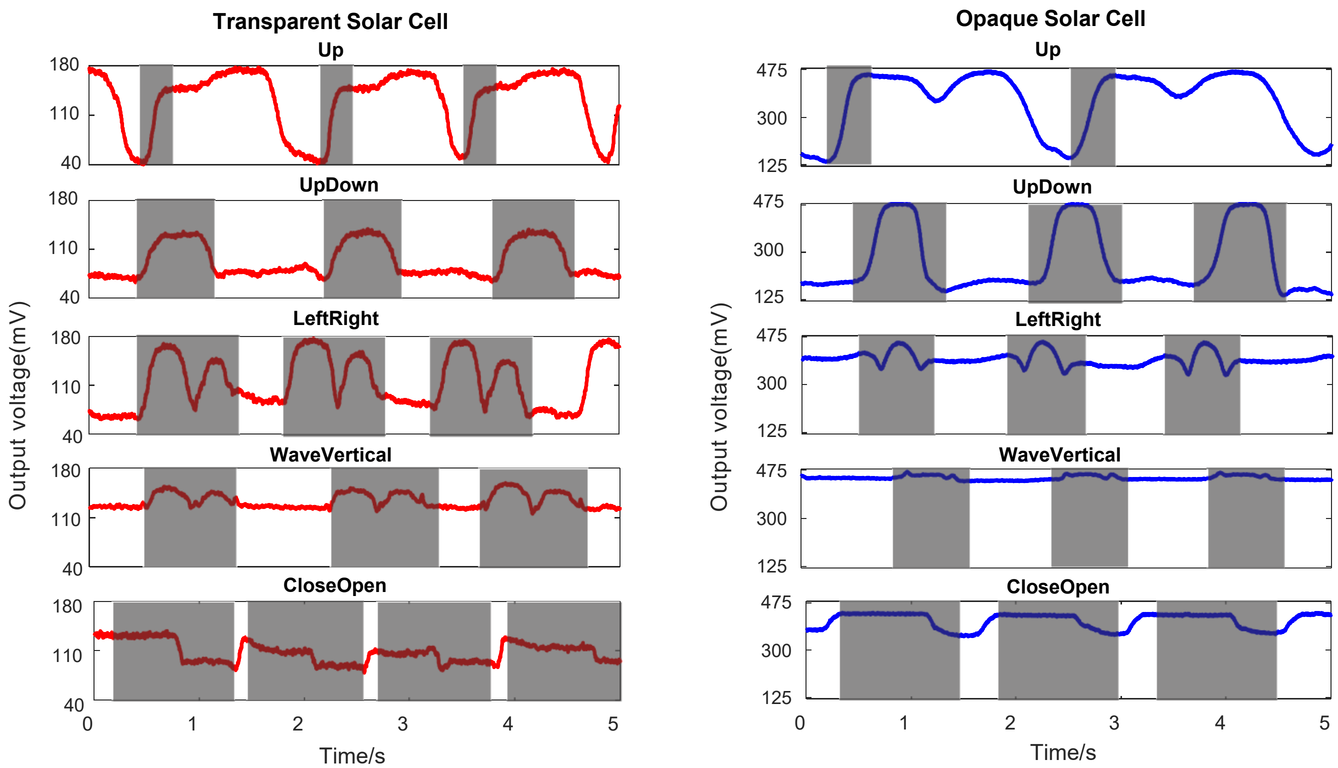


Figure 8: Solar cell voltage output for different gestures. The 5-sec signal contains voltage data from the same gesture repeated back-to-back. The gray area represents the gesture duration.

each gesture, we randomly select 250 feature *vectors*. This process yields a dataset of $3 \times 250 \times 5$ feature *vectors*.

The training and classification are completed using the well-known machine learning platform called Weka [18]. We compare the performance of four well-known classifiers, SVM, KNN, Decision Tree (DT), and Random Forest (RF). We use the *CVParameterSelection* algorithm in Weka to tune the classifier parameters for the maximum performance. For DT, the confidence factor (C) and minimum number of instances (M) are set to 35% and 2, respectively. For KNN, the number of *nearest neighbors* is set to 10. For RF, the number of iterations (I) is set to 100. For SVM, we choose the *quadratic kernel* and configure the *box constraint* to 5. For each classifier, we perform 10-fold cross-validation and present the average recognition accuracy.

3.3 Gesture Recognition Results

Figure 8 shows the solar cell voltage output for different gestures. As expected, the signal strength of the transparent solar cell is severely diminished compared to conventional opaque cell. This is a direct consequence of achieving transparency, which must avoid absorbing visible lights. However, despite the diminished voltage (energy) output, the transparent solar cell is still capable of exhibiting distinguishing temporal patterns for different gestures, which can be exploited for gesture recognition.

Table 3 presents the gesture recognition accuracy of the two solar cells for different classifiers, under light intensity of 500 lux. As expected, achieving transparency in the solar cell trades off gesture recognition accuracy (due to lower SNR change), which is reflected across all the classifiers. It is however surprising to see that even with the transparent solar cell with good visibility (see Figures 1 and 2), we can still recognize hand gestures with 92-95% accuracy depending on the classifier. We also notice that RF performs the best for both solar cells.

Next, using RF, we examine the *confusion matrix* to investigate whether transparency makes it more difficult to recognize some gestures than others. Figure 9 and Figure 10 compare the confusion matrix for the opaque solar cell and the transparent solar cell, respectively. We find that for two gestures, Up and WaveVertical, the transparent cell performs almost as good as the opaque one while the other gestures perform poorly. This finding highlights that, by properly designing the gestures, transparent solar cells can be used as

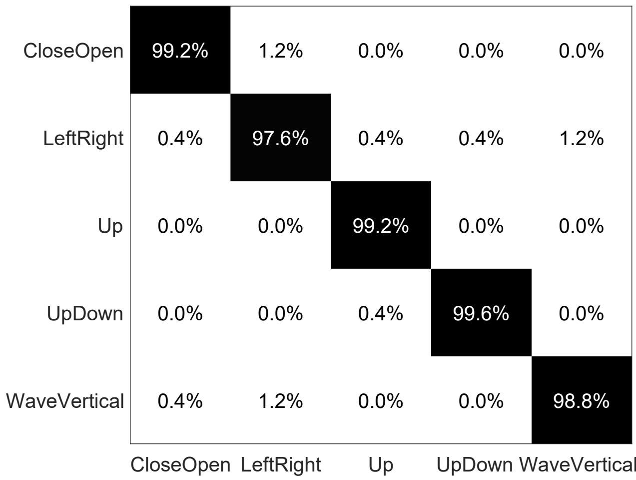


Figure 9: Confusion matrix of gesture recognition using the opaque cell for Random Forest classifier.

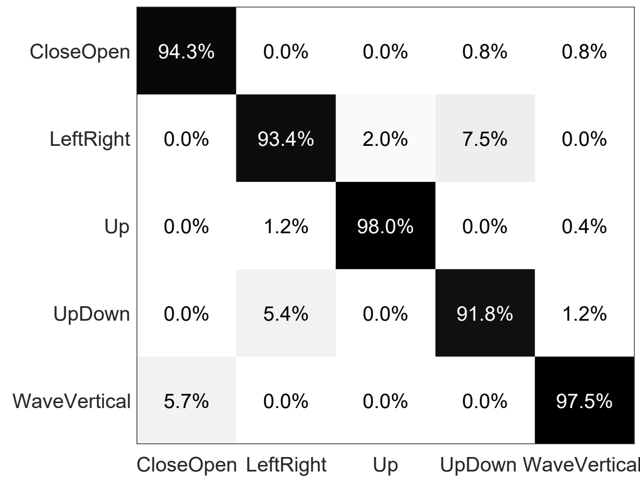


Figure 10: Confusion matrix of gesture recognition using the transparent cell for Random Forest classifier.

Table 3: Gesture Recognition Accuracy.

Classifier	Solar Cell Type	
	Opaque	Transparent
KNN	96.80%	93.52%
Decision Tree	97.76%	92.48%
SVM	94.6%	92.3%
Random Forest	98.88%	94.96%

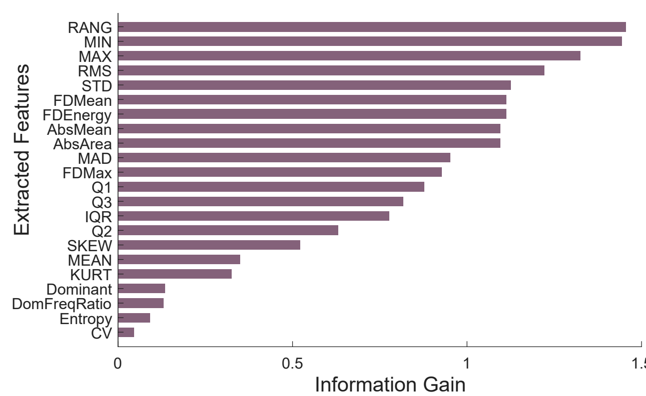


Figure 11: Information gain of the 22 extracted features.

effectively as conventional opaque solar cells for ubiquitous gesture recognition in future smart environments.

3.4 Impact of Light Intensity

To study the impact of light intensity on gesture recognition accuracy, we collected data under two light intensity levels, 500 lux (corresponds to normal office environment) and 2600 lux (corresponds to a cloudy day). We find that the transparent solar cell achieves accuracies of 94.96% and 94.52% under 500 lux and 2600 lux, respectively. Since such accuracy difference should be within the error margin, we can expect transparent solar cells to accurately detect gestures under typical light intensity levels.

3.5 Identifying the Most Informative Features

The previous results are obtained by using all the 22 features shown in Table 2. In this section, we investigate which of these 22 features are the most critical for solar cell based gesture recognition. Figure 11 presents the ranked *information gain* of the 22 features extracted from the gesture *instances* of the transparent solar cell. We can observe that different features indeed have varying importance for gesture recognition. For example, features 'MAX' (the maximum value in a gesture *instance*), 'MIN' (the minimum value in a gesture *instance*), and 'RANG' (the difference between maximum value and minimum value) exhibit significantly higher information gain compared to the rest. Feartures such as 'CV' (coefficient of variation) and 'DomFreqRatio' (the maximum spectral component of the Fourier transform of the signal) seem useless for solar cells to identify the 5 hand gestures. Therefore, based on the ranked information gain, we select the best $n(n = 1, 2, .., 22)$ features and obtain their corresponding

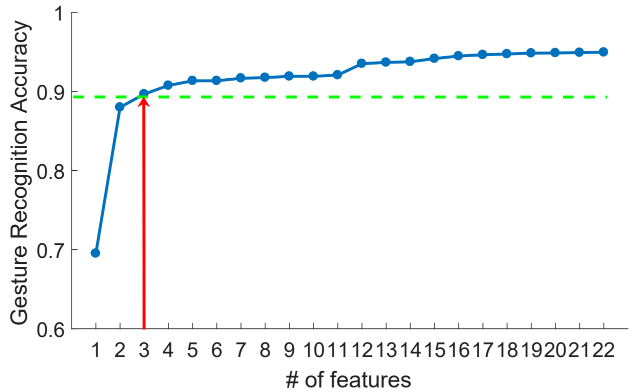


Figure 12: Gesture recognition accuracy of the transparent solar cell for RF as a function of the number of features used from top of the ranked list based on their information gains.

recognition accuracies, as presented in Figure 12. Indeed, we can see that 90% recognition accuracy can be achieved by using only three features, MAX, MIN, and RANG.

4 RELATED WORK

We first review existing research in gesture recognition using various modalities. As solar panels are basically energy harvesters, we also review the literature, which focuses on novel uses of energy harvesters for sensing human actions.

4.1 Gesture Recognition

Gesture recognition has been extensively investigated using a wide range of sensors, such as depth camera [14, 19], accelerometer [13, 20], RF transceiver [10, 21, 22], microphone [11, 23], as well as photodiodes [12, 24–27]. Although excellent gesture recognition accuracy is achieved using such approaches, some limitations impair their practical use. For example, vision based system usually incur heavy computation cost and encounter privacy concerns that arise from the sensitive camera data [28, 29]. Furthermore, additional power budget resulted from the use of sensors (e.g., accelerometer and microphone) impedes its application especially in low-power devices. In contrast, employing solar cells for gesture recognition not only eliminates sensor-consumed energy but also provides inexhaustible power supply to the IoT device. Since both solar cells and light sensor-based gesture recognition rely on visible light, particularly, we next review existing light sensor based works as they share the same modality with solar cell based method, i.e., ambient light.

Exploiting the visible light for gesture recognition has received many interests in recent years. A number of Visible Light Sensing (VLS) based systems, such as StarLight [27], LiSense [26], LiGest [24], and GestureLite [12], have been proposed to either recognize hand gestures within a small range or reconstruct the whole body posture in a room space. The basic principle of these works is that the shadows of different postures under light are distinct. To detect and track the shadow, these systems deploy an array of photodiodes (usually in dozens) on the floor. Some of them also require multiple light sources and the control of the light (i.e., ceiling LEDs) [25–27]. Using the shadow information, different gestures can be recognized or a 3D skeleton posture can be reconstructed in real-time.

The use of photodiodes, however, exhibits two drawbacks. First, photodiodes require an external power supply, which consumes hundreds of uW power. The power consumption is much higher when dozens of photodiodes are used. Second, photodiodes suffer the saturation issue [12, 26, 27], i.e., have a limited response range in terms of light intensity. More specifically, under a bright environment, e.g., direct sunlight, photodiode output is almost stable and no longer reflects the surrounding light intensity. Different from the photodiodes based systems, our work leverages the solar cell as the light sensor to detect hand gestures, which naturally eliminates the above-mentioned two limitations of photodiodes. Moreover, the original functionality of solar cells definitely introduces extra benefit, i.e., harvesting energy from the environment to supplement the system power.

4.2 Human Sensing using Energy Harvesters

Although there are many types of energy harvesters, researchers have mainly used kinetic and solar energy harvesters for detecting various human activities.

4.2.1 Kinetic Energy Harvesting based Sensing. Kinetic energy harvesters convert mechanical energy into electrical current. By scavenging energy from wind, machine vibrations, or human daily activities, existing works have demonstrated the capability to extend battery lifetime of ubiquitous electronic devices [30]. Most recently, many works have investigated the feasibility of using kinetic energy harvester for energy-efficient context sensing. A wide range of applications, such as acoustic communication [31] and human-centered sensing like activity recognition [32], human identification [33], transportation mode detection [34], and airflow monitoring [35], have been studied and demonstrated.

The underlying idea is that energy signals from the energy harvester directly reflect the surrounding context. For example, an insole embedded with a kinetic energy harvester can generate energy from human steps [32]. By analyzing the patterns of the energy signal, different activities such as walking, jogging, and upstairs can be differentiated. Similarly, when putting a vibration energy harvester to the outlets of the air conditioning system, speed of the airflow can be estimated based on the time and frequency domain features extracted from the generated energy signal [35].

4.2.2 Solar Energy Harvesting based Sensing. Based on the principle that solar cell current reflects the surrounding light strength, sensing applications like indoor positioning [36], course-grained localization [37], as well as gesture recognition [15], have been proposed by regarding the solar cell as an alternative light sensor.

In [36], the authors presented the LuxTrace, a wearable solar cell based indoor positioning system. In the prototype, solar cells are attached to the shoulder of the user, which not only harvest energy from the ambient indoor light, but also detect the received light strength (RLS). By utilizing the RLS, a trained model is exploited to estimate the relative distance between the user's location and the light sources. In [37], SunSpot has been proposed to find the location of a solar-powered home to a small region of interest, given the energy harvesting information. The key insight is that every location on Earth has a unique solar signature, like a unique sunrise, sunset time. Thus, with the energy data from the solar cell, the proposed system is able to infer a location's longitude and latitude separately, based on the sunlight map.

The most relevant work is [15], in which the authors utilized an opaque solar cell to identify three hand gestures. Our work differs from it in two aspects. First, we utilize the transparent solar cell that has lower absorption rate in the visible light band. How this characteristic will affect the gesture recognition performance is unknown in prior. Second, although the authors claimed that three gestures (*Swipe, Two Taps, and Four Taps*) are differentiated, their system actually works because the counts (i.e., the number of repetitions of a basic gesture) of the gestures are different. Our work demonstrated that fine-grained gestures can be identified using the transparent solar cell.

5 CONCLUSION AND FUTURE WORK

We have conducted a world first experiment to study the gesture recognition capability of transparent solar cells. Our study has revealed several interesting findings. As expected, achieving transparency in solar cells trades off their gesture recognition capability in general. It is however surprising that transparent solar cells with good visibility (35% AVT) can still recognize hand gestures with 92-95% accuracy depending on the classifier. It is even more surprising that with proper designing of the gestures, transparent solar cells have the capability to recognize hand gestures almost as good as conventional opaque solar cells. Finally, transparent solar cells can achieve these gesture recognition accuracies by extracting only three simple features, the *max*, the *min*, and the *range* of the solar cell voltage output. These findings suggest that transparent solars cells could be potentially used for gesture-based control of many solar-powered objects in future smart environments.

This is a preliminary study to gain some basic understanding of the gesture recognition capability of transparent solar cells. Our plan for future work is as follows:

- As solar cells are deemed to be effective when the light strength is strong, whether they can be utilized for gesture recognition under extremely dark environment, such as dim living room or cinema, should be investigated.
- Since the output current of the solar cell is sensitive to the incident light strength, the movement of people nearby or a sudden change of light intensity might introduce interference to the gesture recognition process, which should be quantified and analyzed.
- The prototype used in our study has an AVT of 35%. For different application scenarios, the AVT values may vary. Therefore, gesture recognition accuracy as a function of AVT should be evaluated.
- In our current work, we used *machine learning* for gesture recognition, which revealed that some gestures are harder to recognize compared to others. In our previous work involving WiFi-based gesture recognition (WiGest) [22], we found that highly distinguishable gestures or family of gestures could be constructed based on some primitives, such as increasing signal strength, decreasing signal strength and so on. It would be an interesting future work to investigate the existence of similar primitives for the solar cell output and use them to design highly accurate gesture recognition algorithms. Such primitive-based gesture recognition will also eliminate the need for training, which will help ubiquitous adoption of such systems in future smart environments.
- In contrast to opaque solar cells, transparent cells can harvest energy from top layer as well as bottom layer. Although we motivated the use of transparent solar cells on the screens of mobile devices, we have not analyzed the impact of backlight (i.e., screen brightness) on gesture recognition. Further experiment should be conducted once the cells can be integrated to smartphone screen.

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