Received WiFi Signal Strength Monitoring for Contactless Body Temperature Classification

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Abstract. Currently, non-contact body temperature monitoring requires specialized thermometers, such as non-contact infrared thermometers (NCIT), to achieve a reading. This work explores an alternative way of classifying temperature using the ubiquitous WiFi waveform. By merely observing the change in the received signal strength indicator (RSSI), body temperature can be classified as below normal, normal, or warm. Using a smartphone as the receiver and a router or another phone as the transmitter, experimental results show that temperature is inversely correlated with RSSI. The findings also indicate that WiFi RSSI is less variable when the temperature is cooler. Our classification can correctly identify the temperature class from a single RSSI reading 56.86% of the time. It can correctly identify a cool reading 61.11% of the time, a normal reading 58.82% of the time, and a warm reading 50% of the time.

Keywords: Body temperature · WiFi · Smartphones

1 Introduction

As a result of the Covid-19 pandemic, there has been an explosive growth of body temperature monitoring in an expanded number of settings. Temperatures, which serve as a proxy for infection, are being taken daily to allow for entry into schools, workplaces, and retails settings.

Body temperature measurement can and has typically been carried out using physical contact with a mercury or digital thermometer. While this method has high accuracy, it requires prolonged contact and sanitation of the thermometer following each use. Commercially available contactless thermometers, known as non-contact infrared thermometers (NCIT), use technology that measures the reflected infrared radiation. They do not require contact but are not as accurate as the contact thermometers.

This paper examines the feasibility of using only smart phones and no other specialized hardware to make contactless body temperature readings. While infrared sensors are cheap and affordable, there are alternative waveforms that are more ubiquitous and universally available on smartphones. In this paper, we focus on WiFi as that waveform.

Due to the ubiquity of smart phones and other mobile devices, people universally have access to a WiFi transducer. In this work, WiFi received signal strength indicator

M. Ur Rehman and A. Zoha (Eds.): BODYNETS 2021, LNICST 420, pp. 112–125, 2022.
https://doi.org/10.1007/978-3-030-95593-9_10

(RSSI) and its relationship to temperature is explored, thus opening the potential for measuring temperature using only the WiFi hardware of a smart phone and an installed app.

In this work, a series of experiments were carried out that measured the RSSI of a WiFi access points as temperature was varied, thus quantifying the relationship between temperature and WiFi signal strength. The experiments showed that the accessibility of temperature monitoring can be improved by leveraging the nature of wireless signals and the infrastructure that comes with living in the digital age.

2 Related Work

2.1 WiFi for Localization

Although, the main functionality of WiFi is to provide wireless connectivity in a local area network, its ubiquity has enabled its expanded use for localization. There have been many studies that evaluate the use of WiFi signals for indoor localization and positioning monitoring [1, 3, 4, 6].

WiFi RSSI is heavily influenced by the environment [13] and so filtering has been shown to improve its effectiveness in localization. Researchers have looked at the improved accuracy of using Kalman [8], Gaussian [9, 10] and newer filters [11] on the smartphones RSSI readings.

2.2 RF Monitoring of Human Vital Signs and Activity

Researchers have previously explored monitoring human vital signs using wireless technology. One such study uses mmWave (60 GHz) RSSI to track human's heartbeat and breathing [2]. A more recent study uses a similar approach to analyzing sleeping posture using RF-reflection [5]. Both studies use reflection and orientation of the subject to determine their vital sign.

In 2016, a study demonstrated the use of radio waves and wearable devices to track a person's activity [12]. A more recent study in 2018 showed how Bluetooth signals can be used to track and classify a person's actions [7], by looking for specific patterns in the Bluetooth RSSI readings.

While WiFi channel state information (CSI) is not available yet for mobile phones, researchers have used CSI to count individuals in a crowd [14]. By leveraging the response of movement by the Channel Frequency Response and using CSI to extract useful information, their trained-once model has an accuracy of 74% to 52% [14].

2.3 Temperature Studies on Wireless Network

The impact of temperature on wireless connectivity has been explored before. Studies have shown that sensor nodes require less energy to transmit during cooler temperatures and are able to maintain a more stable link [19]. In 2013, a study demonstrated the effect of hot temperature on wireless network. It showed that RSSI can decrease up to 8 dBm when measured at 65 °C [17]. Another study in 2013 further explored how temperature can affect the communication protocol and its resulting data transmission rate [18].

2.4 Temperature Sensing Technology

Smartphones are equipped with temperature sensors to monitor internal hardware temperature. A study done in 2015 leveraged this technology to track skin temperature. The researchers were able to achieve 99% accuracy, but their method requires skin-contact and can only track the surface temperature of the skin [20].

Similarly, a study in 2018 used the CPU's temperature to estimate outdoor temperature in a field [22]. They achieved an average error of 1.5 °F.

Chen et al. developed bespoke hardware to monitor body temperature. They use an in-ear thermometer to monitor core temperature with a smart phone application [21]. The sensor is equipped with an infrared thermometer which transmits the temperature readings to a paired app.

As for contactless temperature monitoring, other than commercially available NCIT devices [15, 16], contactless temperature monitoring requires visual cues and an RGB-thermal camera [23].

3 Approach Overview

In this work, to measure an individual's body temperature, the person is positioned between a WiFi transmitter and a WiFi receiver; and the change in the WiFi reading is used to classify the person's body temperature as below normal, normal, or warm. As shown in Fig. 1, the person stands in front of any WiFi access point and a smartphone is used to examine the change in the WiFi received signal and determine if the person is warm.

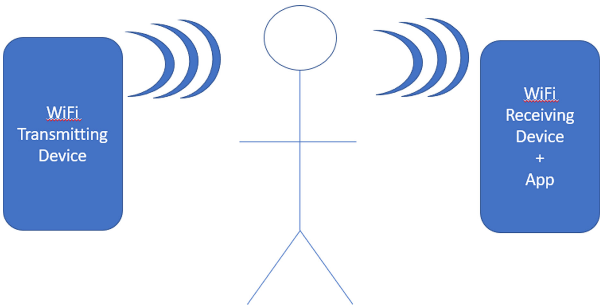


Fig. 1. System overview with the person stepping between a WiFi transmitter and a WiFi receiver to determine the person's body temperature, as observed in the changes with the WiFi received signal strength.

For the system prototype, a bespoke software app was developed that monitored the WiFi received signal strength. Both the signal strength and its change over time were used for classification.

The WiFi received signal strength indicator (RSSI) is reported in decibels in relation to milliwatts (dBm). The range of the reference typically falls between –30 dBm and –100 dBm but can approach 0. The stronger the signal, the larger and the less negative the reading.

4 Experimental Set-Up

A software app was developed that records the RSSI reading over time with a sample rate of approximately one scan per every 3 to 4 s. It carries out a WiFi scan for access points. Upon receipt of a result, the app records the strength and the time of the receipt for each access point that it has found.

The experimental setup utilizes two separate devices, with one designated as the WiFi wireless signal transmitter and the other as the WiFi wireless signal receiver. A Samsung Galaxy S10 was used as a receiving device. Depending on the experiment, either a SageCom Router as an access point or a Samsung Galaxy S10e smartphone was used as the transmitting device.

Downloading or uploading data can cause interference in the reading of RSSI. Therefore, both devices were disconnected from any mobile network. The phones were not connected to the internet during the experiments. The receiving phone is not paired with any wireless devices or networks. WiFi scan throttling is disabled to ensure continuous scan.

The model collects multiple RSSI readings for analysis. The collected RSSI in dBm is plotted onto a graph and the slope of the regression line is used to determine the overall trend of the dBm. Any spikes or oscillations within the reading is recorded, except for outliers that lie far beyond the clustered set of data.

5 Experiments

Three different types of experiments were carried out. In the first two experiments, changes in a bowl of water's temperature were used to simulate the human body. In the first experiment, the smart phone recording the WiFi RSSI was placed near the bowl of water, while in the second experiment the smartphone was submerged in the bowl. The third set of experiments measured the temperature of a human hand, after it was dipped in ice water and dipped in warm water.

5.1 Water Bowl Experiments

The first experiment involved changing the temperature of a bowl of water and observing changes in RSSI. A bowl of water is placed in between two mobile devices. The devices are placed equidistant from the foot of the bowl. The receiving phone simultaneously keeps track of the signal dBm from both the transmitting phone and the router. An aquarium thermometer is submerged in the water bowl to monitor the water of the temperature. Figure 2 illustrates the setup of the experiment.

The experiment was carried out three times using three different water temperatures: hot, cold, and room temperature. Cold is defined as having water temperature of 44.2 °F to 46.9 °F. Room temperature is defined as having water temperature of 73.5 °F. Hot is defined at having temperature of 131 °F to 149.5 °F.

Fig. 2. Two smart phones are placed equidistant from the foot of the bowl. An aquarium thermometer is placed submerged in the water to monitor the water of the temperature.

The graph in Fig. 3 shows the RSSI under the effect of cooling hot water. A total of 65 samples were collected over the course of 4 min. The initial temperature of the water was 149.5 °F, which fell to 131 °F by the end of the observation period. The average dBm for this round was −23.1538.

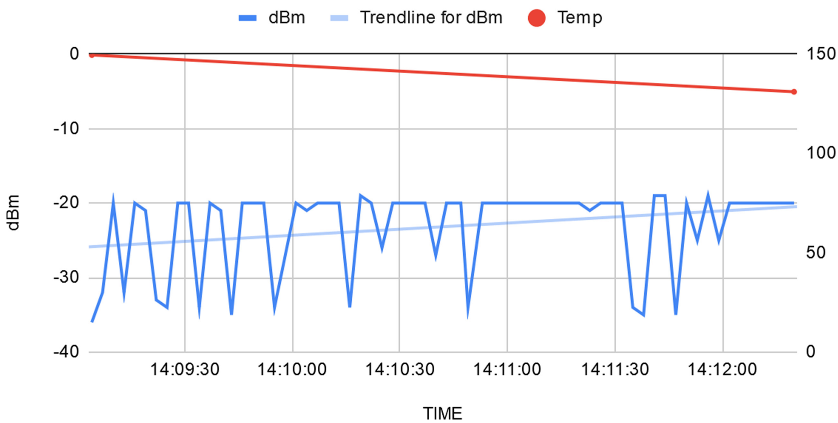


Fig. 3. Signal and temperature over time for hot water. Slope shows a positive slope in relation to the decrease in water temperature.

In Fig. 3, the overall trendline for the signal shows a positive slope. Despite the oscillation of signal, as temperature decreases, there is a slight increase in signal strength. Also, the RSSI variability decreases as the temperature decreases.

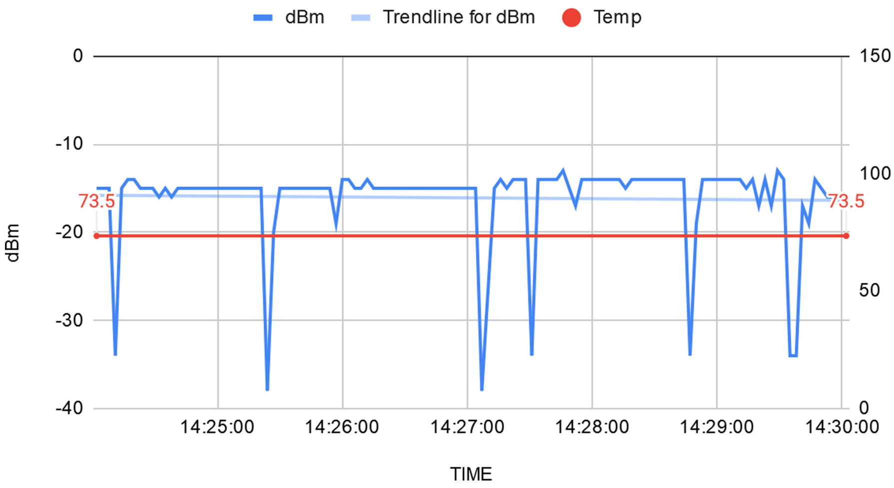


Fig. 4. Signal and temperature over time for room temperature water. Signal is relatively stable with room temperature water.

Figure 4 shows the RSSI readings for the room temperature water. The signal remains stable, which is in line with the water temperature which is also kept stable throughout the observation period, remaining at a constant 73.5 °F. A total of 75 samples were collected over the course of 6 min. The average dBm for this round was −16.0181.

Figure 5 shows the RSSI readings for the cold water. The RSSI is relatively constant. Although temperature increases by a small amount, this is not reflected in the slope of the trend line. A total of 75 samples were collected over the course of 4 min. The initial water temperature was 44.2 °F, which gradually increased to 46.9 °F. The average dBm for this round was −14.5811.

Table 1 gives the average and the standard deviation of the WiFi RSSI for the three different temperature tests. Comparing the results from the three different instances, an inverse relationship between temperature and WiFi RSSI is observed. The results show an inversely linear relationship between temperature and average signal strength. As temperature increases, not only does the signal strength decrease, but the variability also increases.

5.2 Submerged Water Bowl Experiments

To further isolate the key hypothesis, the smart phone was submerged into a bowl of water to record the change in RSSI. The water was boiled and left to cool naturally during the observation period. The phone is placed within 2 resealable plastic bags to prevent water from damaging the phone. It is then placed submerged into the bowl. There

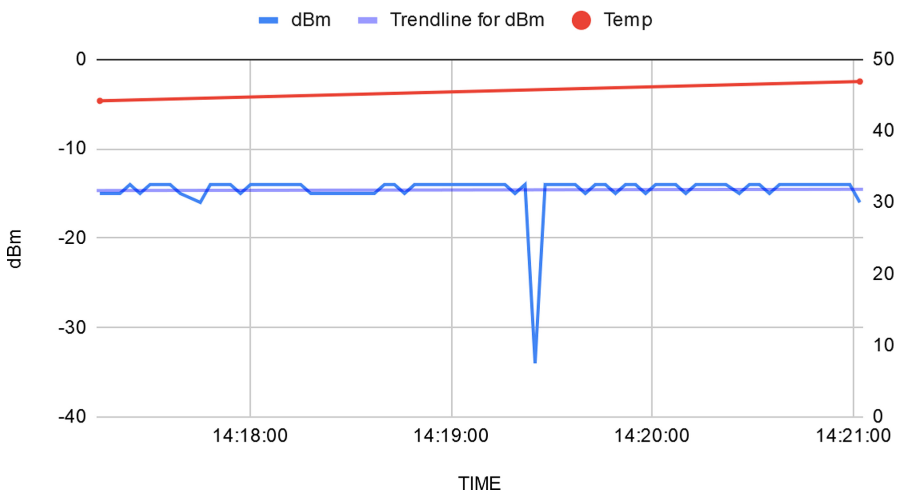


Fig. 5. Signal and temperature over time for cold water. Signal is relatively stable with cold water, despite small increase in water temperature over time.

Table 1. Average RSSI, standard deviation, small size, temperature, and time span for the three water temperatures.

Water temp	Average RSSI	RSSI STDEV	Sample size	Start temp	End temp	Time span
Cold	−14.58108108	2.330757909	75	44.2	46.9	4 min
Room temp	−16.08108108	4.869467292	75	73.5	73.5	6 min
Hot	−23.15384615	5.67403838	65	149.5	131	4 min

is ample space between the bottom of the bowl and the phone, as shown in Fig. 6. A temperature sensor is placed inside the bowl as before.

Figure 7 shows the RSSI as the water temperature changes. A total of 549 samples were collected. The initial temperature of the water was 108.1 °F, which fell to 92.9 °F by the end of the observation period. When the water temperature reaches 96.6 °F, there is a noticeable stabilization effect on the reading. The overall regression line follows a positive slope as temperature falls. Figures 8a,b show that when the water temperature remains constant, the RSSI signal remains constant as well. These results match with the finding from the previous experiments and confirms the hypothesis that temperature does affect RSSI of the WiFi signal. The experiment also shows that signal strength's variability decreases in cooler temperatures. As temperature decreases, the WiFi signal increases.

Fig. 6. Smartphone submerged in water bowl with an aquarium thermometer to monitor the water of the temperature.

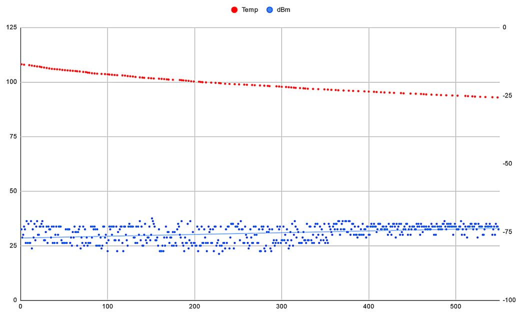


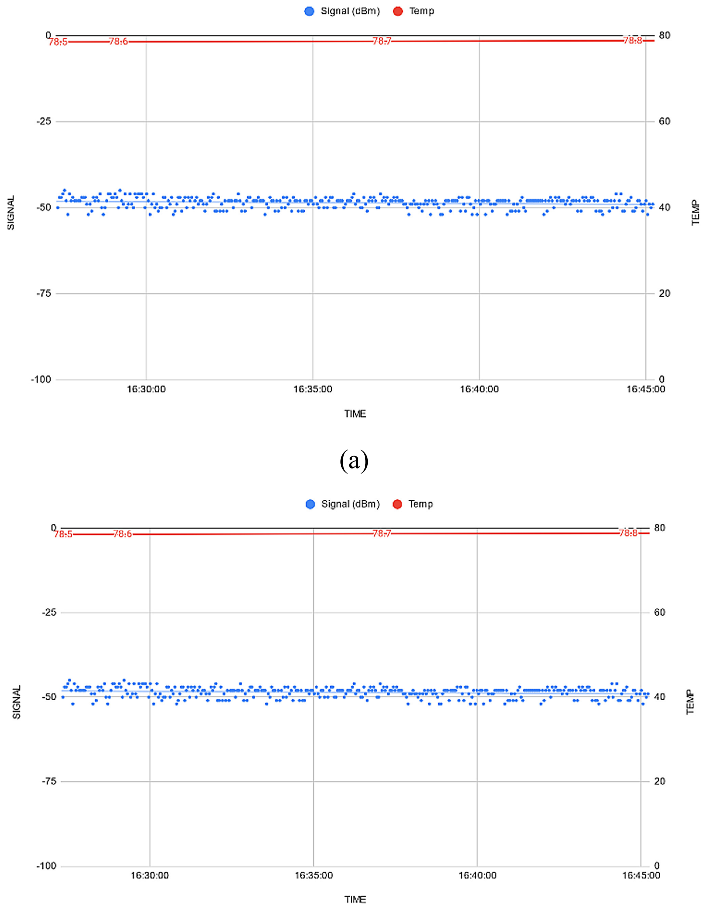
Fig. 7. Signal and temperature over time for bowl of water. RSSI increases and its standard deviation decreases as the temperature increases.

5.3 Hand Experiments

In the next series of experiments, the presence and the temperature of a person is measured using changes in WiFi RSSI. The person's hand is used for the experiment, as it can be cooled or warmed by dipping the hand into cold and warm water.

The setup, as show in Fig. 9, includes two phones facing away from each other. Due to the location of the WiFi adapter on the devices, this orientation has the strongest baseline signal. In the experiment, the person places the hand in between the two phones equidistant from both phones for a period of seconds before removing the hand.

There are three classes of temperature. There is the hand at normal temperature. There is the hand dipped in ice water which has a cool temperature. There is the hand dipped in warm water, which results in the hand having a warm temperature. Following



(a)

(b)

Fig. 8. Signal and temperature over time for bowl of room temperature water. Signal is relatively stable with room temperature water.

the dipping into water, the hand is quickly dried and then placed exactly between the two phones. The placement is kept for at least 4 s due to the limitation of WiFi Scanning of the hardware.

Due to heat loss or heat gain, the exact temperature of the hand at the time of detection is not possible to isolate. Instead, the reading of the hand is taken just before and after the detection to ensure the closest temperature estimation. There are three temperature group for each of the test run, cold, normal, and warm. The respective temperature range for them are, 82 °F to 84° for cold, 98 °F for normal, and 103 °F to 104 °F for warm. A total of 4 separate trials were run.

As shown in Fig. 10, a person standing in between the two smartphones can be detected. This indicates the need to isolate change in RSSI caused by obstruction from the change in RSSI caused by temperature changes.

Fig. 9. Two smart phones are setup to face one another so that the WiFi adapter have direct access. This orientation is found to have the clearest signal reception.

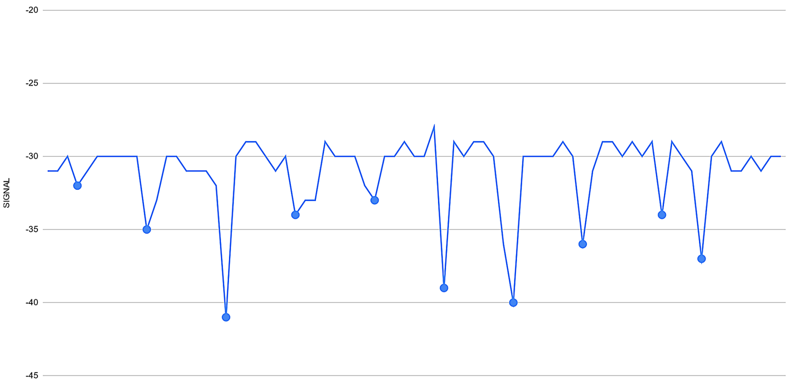


Fig. 10. The RSSI reading over time, as a person steps between the two devices. The dots indicated the moment of detection of the person. All 10 instances of the human obstruction are successfully detected.

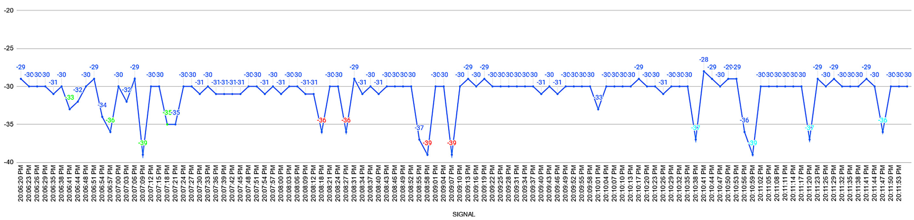


Fig. 11. Signal and temperature for the 1st hand trial.

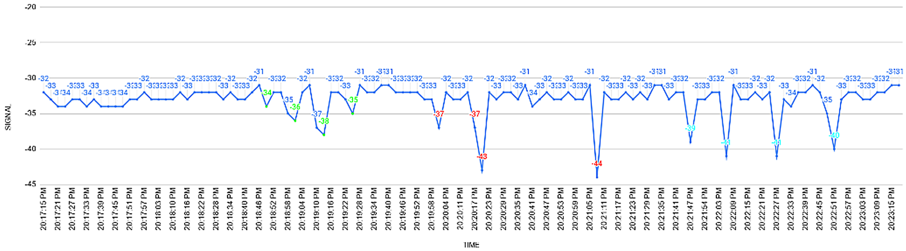


Fig. 12. Signal and temperature for the 2nd hand trial.

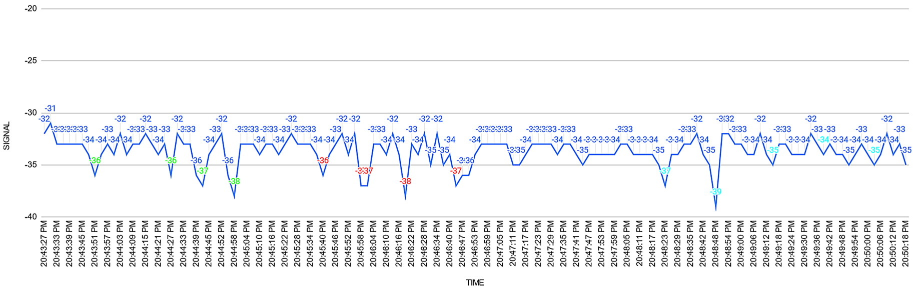


Fig. 13. Signal and temperature for the 3rd hand trial.

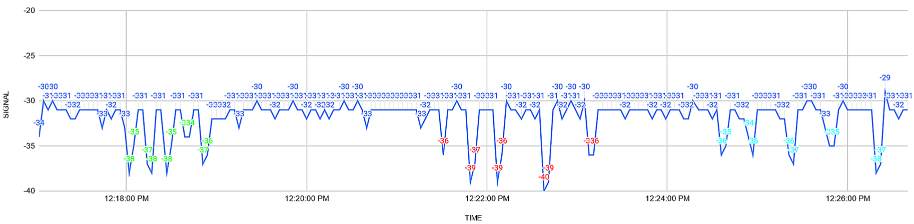


Fig. 14. Signal and temperature for the 4th hand trial.

Four trials were carried out with the results shown in Fig. 11, Fig. 12, Fig. 13, Fig. 14. In the figures, each color-coded entry indicates the detection of the hand. Green signifies normal temperature, which is 98 °F. Red signifies a temperature reading of 103 °F to 104 °F. Cyan signifies a reading of 82 °F to 84 °F.

For the first trial, there were 4 instances for each temperature class and all twelve instances were detected. For the remaining trials, there were 5 instances for each temperature classes, and an average of 80% of the instances were detected. Table 2 gives the average and standard deviation of the readings for the four trials.

In all the trials, WiFi RSSI is larger under cool temperature than warm temperature. Additionally, there is a smaller standard deviation at cooler temperatures. These experiments are therefore successful in isolating the obstruction element from the temperature element.

Table 2. RSSI reading average and standard deviation for the cool, normal, and warm hand experiments across the four trials.

	Trial #1	Trial #2	Trial #3	Trial #4
Average cool temp	−36.875	−40.25	−36	−35.9
STDEV cool temp	0.6291528696	0.9574271078	2	1.197219
Average normal temp	−35.5	−35.25	−36.375	−36.2
STDEV normal temp	2.516611478	1.658312395	0.4787135539	1.619327707
Average warm temp	−37.25	−40.33333333	−36.83333333	−37.55555556
STDEV warm temp	1.5	3.511884584	0.8819171037	1.666666667

5.4 Hand Temperature Classification

To classify an RSSI reading as either cool, normal, or warm temperature, a baseline range for normal temperature is determined. The readings are classified as warm, if the RSSI is less than the baseline's minimum value. The readings are classified as cool, if the RSSI is more than the baseline's maximum value. The readings are classified as normal if they are within the baseline's range.

Table 3 shows the confusion matrix for the total 51 samples across the four trials. A cool reading has a 61.11% chance of being correctly identified. The chance of being misclassified as normal is 5.56% and the chance of it being misclassified as warm is 33.33%. A normal reading has a 58.82% of being correctly identified. The chance of being misclassified as cool is 29.41% and being misclassified as warm is 11.76%. The A warm reading has a 50% chance of being correctly identified. There is a 43.75% chance of it being misclassified as cool and 6.25% chance as normal. Overall, there a 56.86% chance of a reading being correctly identify. This is an improvement from the 33% chance of randomly guessing from among three temperature group.

Table 3. Classification confusion matrix

Predicted	Cool	Actual normal	Warm
Cool	**61.11%**	29.41%	43.75%
Normal	5.56%	**58.82%**	6.25%
Warm	33.33%	11.76%	**50.00%**
Overall accuracy		**56.86%**	

6 Conclusion

We explored the impact of temperature on WiFi signals, as measured with commercial smartphones. The experimental results confirm that temperature does influence received WiFi signal strength and signal variability and thus can be used to classify temperature. A classification accuracy of 56.86% was achieved on a single reading across a three-class library of cool, normal, and warm.

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