The Impacts of Humidity and Temperature on RSSI in a Close Indoor Environment and Neural Network Modeling of the Relationship

Anisha Jain
anisha.j149@gmail.com

Abstract

Contact tracing and proximity detection are tools for preventing the spread of viruses, and in the time of the coronavirus pandemic this remains true. Bluetooth RSSI values are being used to detect proximity but are susceptible to fluctuations due to environmental factors which can make it unreliable to perceive distance. We conducted this study in order to research the limitations of this technology. We hypothesized that humidity and temperature would have an effect on RSSI values and studied these variables in an indoor and close environment. We found strong correlations between the variables with linear regressions, but using ANOVA test and t-test, we were not able to find enough evidence of causation. Additionally, we wrote a script that took advantage of the correlations between temperature and humidity and RSSI to create a feed forward neural network that predicts RSSI values based on temperature and humidity.

Keywords: RSSI; Humidity; Temperature; Proximity; Indoor

1. Introduction

The coronavirus pandemic has caused immediate need for pragmatic technologies for contact tracing and proximity detection, as both are important tools in mitigating the consequences of an infectious virus. Contact tracing, ordinarily a time-consuming and error-ridden process when done by memory, looks back in an infected individuals past to see if the individual may have come into close contact with another person and infected them in order to warn that person of possible infection. Contact tracing's accuracy could be improved with Bluetooth to detect exactly when or if the individual came into close proximity with another person. However, according to Klienman and Merkel, there can be significant fluctuations in bluetooth signal strength, measured with received signal strength indicator (RSSI), based on hardware, location, obstacles, weather (the outdoors), etc. RSSI can be used to infer distance between the transmitter and receiver, so fluctuations are important to study for proximity detection (2020). Bluetooth's limitations should be studied further so developers can utilize Bluetooth in the most effective and accurate manner to curb the Coronavirus pandemic and other infectious viruses.

2. Related Works

Many studies have tested the effect of humidity and temperature on RSSI in different environments. Guidara, Fersi, and Derbel, testing the effects of temperature and humidity in an indoor environment, concluded that temperature has a strong negative correlation with RSSI and humidity tended to have a strong positive correlation with RSSI (2018). Luomala and Hakala, testing in an outdoor environment, supported these claims, but they suggested that humidity's correlation was not that strong. They added that, while temperature seemed to be the most impactful variable, high relative humidity had some effect at sub zero temperatures, suggesting that at room temperature, humidity has little effect (2015).

Humidity and temperature's effect was also studied in different distances between the sender and receiver. Humidity and temperature seemed to have a greater impact on RSSI when the distance between the sender and receiver is large, but at small distances of 3m and below, the variables have little to no effect on RSSI (Guidara et al. 2018).

Both studies have studied the effects of temperature and humidity simultaneously because the variables are interconnected. There is no way to isolate the two in the home environment, so they will be used as two different measurements of one independent variable introduction of steam into an environment for the purpose of statistical analysis.

3. Purpose of Experiment

This study tests humidity and temperature's effects on RSSI in close indoor proximity to confirm the correlations that many past studies have deduced.

An indoor and close environment was chosen because this paper aims to study RSSI in risky circumstances for the coronavirus. The Center for Disease Control and Prevention (CDC) has suggested a 6 feet, or approximately 2 meter, distance between individuals to avoid spreading coronavirus, so this paper will use a short distance to study Bluetooth RSSI. Additionally, Quian et al. in a preprint article found that outdoor infection was incredibly rare and most infections occured indoors which is why this research was conducted in an indoor environment (2020). In these conditions, the research may be more relevant to developers who aim to use Bluetooth and RSSI to curb the ongoing pandemic.

a. Hypotheses

- Null hypothesis: Temperature and humidity have no effect on RSSI value.
- Experimental Hypothesis: Temperature and humidity have an effect on RSSI value.

Relevant aspects: Humidity, temperature, RSSI values

b. Neural network

Constructing a neural network that can predict the RSSI value based on what is found in the experiment can be helpful for those developing technology to combat the coronavirus.

4. Method

The experiment was carried out in a 2.5 x 1.5 meter room with two Raspberry Pis placed in a diagonal formation such that one Pi was higher than the other so that the humidity that may permeate the room in an uneven manner could have a somewhat even effect on the RSSI value. The Pis were placed at a distance of 3 meters from each other. We previously programmed the Pis to scan for and advertise beacons using bluetooth, and connected to them with laptops with Secure Shell so we could run the programs wirelessly. The relative humidity and temperature were recorded. We ran the Raspberry Pi programs for 20 seconds and recorded the resulting RSSI values. We then increased the relative humidity by 10% by running hot water from a nearby tap in the fully enclosed environment. The process of running the program and recording the values was repeated for this relative humidity level and each succeeding level of humidity thereafter.

5. Analysis of Results

Table 1
Descriptive statistics

	1 - Control	2	3	4	5	6
Relative Humidity (%)	50	60	70	80	90	100
Temperature (ºC)	22.778	24.056	24.889	25	25.278	25.667
Mean RSSI	-68.333	-71.947	-70.25	-69.63	-74.05	-71.26
Maximum RSSI	-56	-64	-63	-63	-66	-63
Minimum RSSI	-82	-82	-77	-82	-84	-80
Range	26	18	14	19	18	17
Standard Deviation	7.670	5.338	3.726	5.344	4.478	4.747

Observations	18	19	20	19	20	19

Relative humidity and temperature were the independent variables and the RSSI values was the dependent variables. The standard deviation differed somewhat, but the control, group 1, differed the most. It also has the greatest range, far greater than the other groups. Although ANOVA is robust, this difference in variation still may be problematic for statistical analysis.

Table 2

Statistical analysis

One-way ANOVA (Analysis of Variance) Test						
p-value	.01211					
Two Sample T-Test p-values						
	1	2	3	4	5	6
1		0.10826	0.34518	0.020309	0.016888	0.17598
2			0.26030	0.32291	0.19233	0.67884
3				0.027074	0.00599	0.46503
4					0.81859	0.14867
5						0.06758
6						

Note: α = .05

We conducted an ANOVA, or analysis of variance, test to identify if there was any statistical significance in the data so that we could reject the null hypothesis. We used the p-value for this determination, as the p-value represents the probability that such a difference in means or extreme occurrence would occur if the null hypothesis was true. We received a value of 0.01211, which was less than our pre-set α (.05), so the data is statistically significant and we should be able to reject the null hypothesis.

In order to analyse the data further, we conducted two-sample t-tests between all levels to find which levels were statistically significant. Few were significant, as highlighted in table 2 in purple. Group 4 and 5 have statistically significant differences with both group 1 and 3. This lack of consistent difference in the data clouds judgement of it. While there clearly is statistical significance in a few group, because these are few in number, more testing should be done in the case that the groups were significant by chance. Therefore, we fail to reject the null hypothesis.

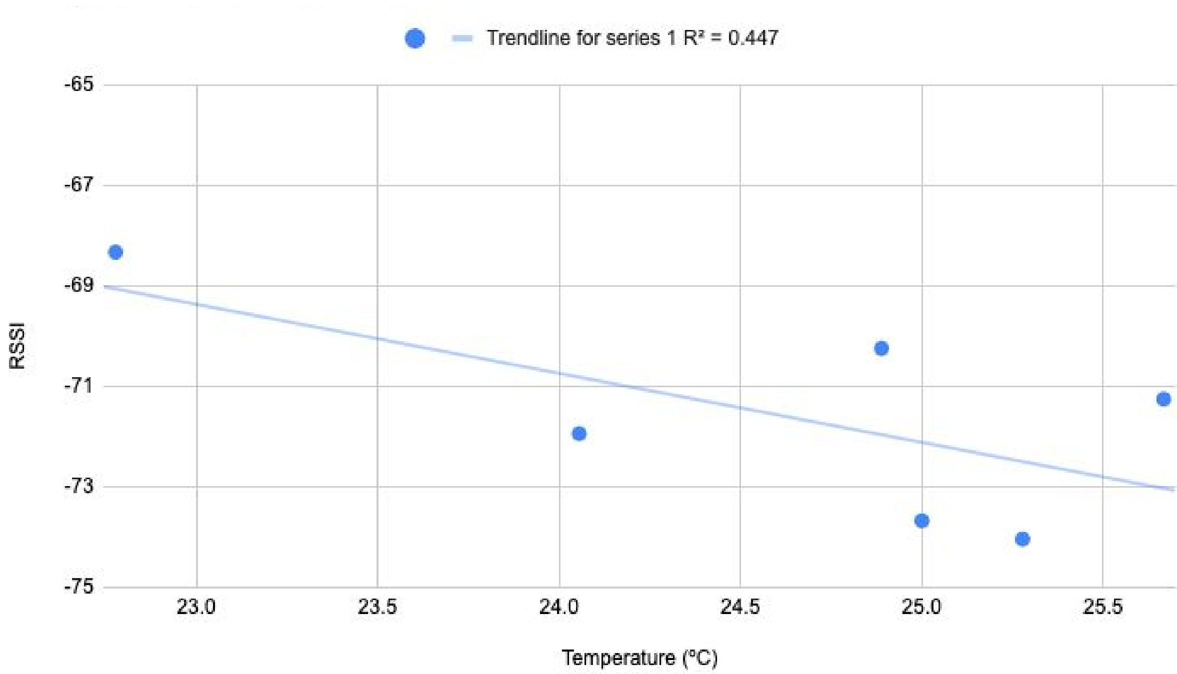

Figure 1. Mean RSSI for the increasing humidity.

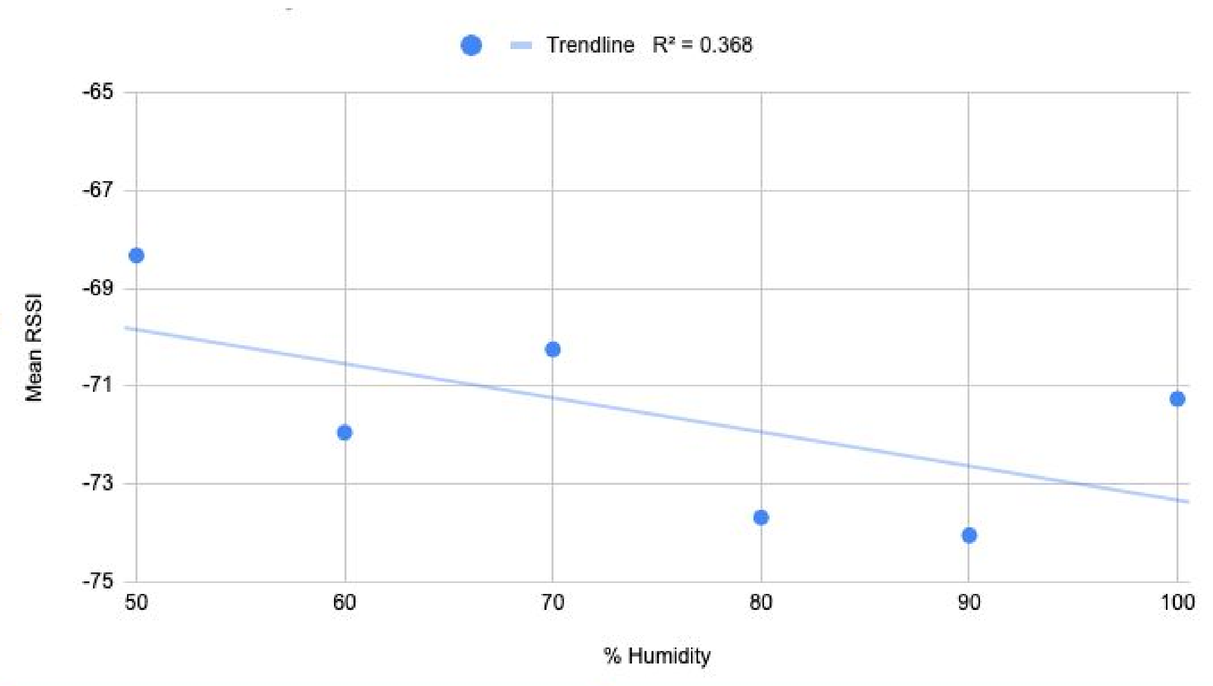

Figure 2. Mean RSSI for the increasing temperature.

Table 3

R^2 and r values for Humidity vs. RSSI and Temperature vs. RSSI

	Humidity vs. RSSI	Temperature vs. RSSI r squared
r^2	0.368	0.447
r	-0.607	-0.669

The relationships in figure one and two were modeled with linear regressions to study the correlations between the variables. Notably, both humidity and temperature have a negative relationship with RSSI. Using r^2 as indication of the strenth of the linear regression, the relatively low r^2 for both figures show's that the linear regression may not be the best model to describe the behavior of the RSSI values. Relatively little of the variation in the data can be explained or accounted for by the linear regression.

Both temperature and humidity have strong negative correlations with RSSI, as shown by their respective r values that are below -0.5. However, shown by table 3, temperature has a much stronger correlation with RSSI than humidity does. Overall, this shows a strong relationship between both variables and RSSI.

6. Discussion

In this experiment there is no way to deduce causation, as in, we would never be able to know if humidity or temperature had an effect, or if together they had an effect, only if some causal effect was possible. Although the ANOVA test showed statistically significant difference and we should have been able to reject the null hypothesis, in reality, when analysed through the T-tests, we found very little statistically significant differences. Without consistent difference throughout, we cannot reject the null hypothesis. Also, the sample sizes in the experiment were small. This could have lead to false positives in the statistical analysis due to the slightly differing deviations.

The experiment did find strong correlations between relative humidity and RSSI and temperature and RSSI. This was consistent with past research. However, as mentioned previously, studies have shown that while temperature has a negative correlation with the RSSI values, humidity has a positive correlation with RSSI, which is inconsistent with our findings. We found that both humidity and temperature had strong negative correlations with RSSI. However, this can be explained by the stronger correlation that temperature has with RSSI both in our data and in Luolama and Hakala (2015), as mentioned. If temperature and humidity have causal effects, then temperature's negative relationship is likely overpowering the smaller positive effects that humidity has.

In addition, Guidata et al. findings seem to be consistent with ours somewhat. The data's lack of strong statistical evidence but strong correlation emulates their findings at the three meter distance between the sender and receiver.

Our imprecise instrumentation may have skewed the data somewhat. The hygrometer used was of low quality, and while it seemed to increment appropriately with the introduction of water vapor in an environment, it likely was imprecise. For example, the control was 50% relative humidity for room humidity, when normally the humidity in a regular living environment is kept at normally 40%. This may be different in locations where hot water is regularly collected in large quantities like the environment where the experiment was conducted, but due to the low monetary cost of the hygrometer, it was likelier than not of low quality.

7. Neural Network Model Fitting

In order to extrapolate the correlations between temperature and humidity, we wrote a script that constructs a neural network based on the data that we found. This could be a better model because the linear regression was shown to be an unrealistic model, and depending on the environment, this different model may be necessary. The neural network created is fairly simple with only three layers nine weights and and currently relies only on the data collected in this study, but with more data and greater complexity it could be much more helpful. Those in table 4 will only work with an input of something in a similar environment.

The script attempts to avoid overfitting by only using a select portion of the data while testing with all of it. The script can produce a neural network that tests all testing data with cost of less than 0.001. Cost refers to the sum of the errors in the what the neural network produces and the actual value expected. With such a small size of data, this neural network is very far from an ideal model.

Table 4

Examples of Neural Networks Produced by Neural Network Script

Neural Network	Cost
[0.8104097018465714, -0.23883677344889023, -0.39065050696962267, 0.5162495496716482, -0.9649046042372725, -0.5334403195358157] [-0.0815343949746098, 0.48720028462905235] [-1.3295518559828152]	0.00097
[-0.5368721868833708, -0.5742214749567472, -0.49628098803047477,	0.00090

-0.46888881801093496, -0.28110146542671666, 0.5799802305074236] [-0.007221572546990762５, -0.39872527356671633] [-1.604801177426697]	
[-0.5670418702704633, 0.48462286113746506, 0.8117096603847961, 0.3461689620821376, 0.055906885630762924, -0.6296865387045532] [-0.23794829382806876, -0.01632130147824477] [-1.5507269327148832]	0.00099

The neural networks differ quite a bit from one another, and this is likely due to the small data size. With a large data set to pull from, there will likely be less inconsistencies.

8. Conclusion

In this paper, we cannot determine wether or not temperature or humidity have an effect on the RSSI value, as the statistical analysis was wishy-washy. However, we were able to observe strong correlations in the the data with with humidity and RSSI and temperature and RSSI. We were able to confirm the stronger relationship that temperature has with RSSI than humidity has with RSSI as well.

In future experiments, higher quality instruments and larger samples should be used. In addition, a laboratory environment that can isolate the variables humidity and temperature so that proper statistical analysis can occur would be beneficial. Further experiments should test the interactions of the variables as well. In addition, with more data collected, a more robust neural network could be constructed.

References

Guidara, A., Fersi, G., Derbel, F., & Jemaa, M. B. (2018). Impacts of Temperature and Humidity variations on RSSI in indoor Wireless Sensor Networks. *Procedia Computer Science, 126*, 1072-1081. doi:10.1016/j.procs.2018.08.044

How to Protect Yourself & Others. (n.d.). Retrieved from https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/prevention.html

Kleinman, R. A., & Merkel, C. (2020). Digital contact tracing for COVID-19. *Canadian Medical Association Journal, 192*(24). doi:10.1503/cmaj.200922

Luomala, J., & Hakala, I. (2015). Effects of Temperature and Humidity on Radio Signal Strength in Outdoor Wireless Sensor Networks. *Proceedings of the 2015 Federated Conference on Computer Science and Information Systems*. doi:10.15439/2015f241

Qian, H., Miao, T., Liu, L., Zheng, X., Luo, D., & Li, Y. (2020). Indoor transmission of

SARS-CoV-2. doi:10.1101/2020.04.04.20053058