Statistical Visualization for Interactions Between Radio Frequency Signal Strength and Environment

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Abstract. This technological record considers the signal strength and wifi strength data and relates this information to other factors that may impact the strength of radio frequency. It is shown how tools can be used to obtain smooth estimators for nonlinear trend analysis. The approach models signal strength and Wifi strength as smooth functions of weather conditions, such as wind speed and temperature. The additional visual effect of antenna type, device type, modulation, device status, and interference type was also illustrated.

Key-words: Estimation; software; splines; WiFi strength.

1. Introduction

WiFi and radio frequency (RF) signal strength monitoring deserves attention for understanding the impact of their widespread use in implementations. It is showcased that for signal and WiFi strength there are several visualization approaches that can be performed to monitor the conditions gathered from devices that collect signal data.

Signals are now encountered in many aspects of people's lives, such as health, communication, entertainment, and education. Some applications of RF signals also include technology [1] for detection of sleep, detection of falls, gesture recognition, radar imaging, and gait recognition. The use of radio frequency can also be extended to device authentification, tracking, autonomous vehicles, and unmanned aerial vehicles [2].

The abundance of uses of radio frequency signals stresses the importance of studying some important factors that impact their strength in studying their functionality. Signal strength has been associated with environmental characteristics, such as temperature, humidity, weather patterns, and wind speed.

The work contains a study in illustrating how to apply available software for nonlinear trend analysis. The paper was organized as follows. Section 2 describes the approach used for statistical modeling. Sections 3 through 7 contain results from applications. Conclusions are posted in Section 8.

2. Approach

2.1. Curvilinear Patterns

The focus of this analysis is to consider radio frequency data and model the response y to be the strength of the radio frequency signal. The signal strength refers to the strength of the RF signal in decibel milliwatts (dBm). The WiFi strength refers to the strength of the WiFi signal at the location of the signal observation in dBm.

The effects of environmental conditions that may impact the signal strength were under investigation in diverse studies. For example, a study was reported in Africa on the impact of humidity on radio signal while studying the relationship linearly [3]. In another study in Malaysia [4] numerical summaries were reported for linear associations and some graphics depicted nonlinear relationships between radio signal strength and wind speed. A study performed in the United Kingdom [5] found that a negative association was observed between signal strength and wind speed.

Signal strength observations could be recorded together with other data related to the environment. The notation y is used here to denote the radio frequency signal strength, and x to denote temperature. The approach considers flexible modeling strategies where the expected value of the signal strength y is related to the variable x in a model of the form $E(y|x) = f(x)$. The $E(y|x)$ notation stands for the conditional mean, or expected value, of y given x.

Our focus is to visually represent the association as estimated by the function f. The paper displays smooth trend estimators and the corresponding uncertainty as estimated by the software. In this presentation x was taken to denote temperature, but other variables were considered as well, such as wind speed, precipitation, or humidity.

2.2. Representation of Smooth Functions

This section contains details pertaining to the strategy of modeling curvilinear trends. Spline basis functions were used to express $f(x)$, that was allowed to be a nonlinear function of x. Basis function expansions were used to represent the function f, as given by the equation

$$f(x) = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 + \sum_{k=1}^{K} b_k (x - \kappa_k)_+^3,$$

where b_k are the coefficients for the cubic spline basis functions with knots at κ_k on the domain of the x variable. The outlook of these basis functions are as follows. Value of $(x - \kappa_k)_+^3 = (x - \kappa_k)^3$ if $x > \kappa_k$ and zero otherwise. Coefficients β_1, β_2 and β_3 correspond to cubic polynomials. For the estimation of f when using the cubic spline basis functions, some portions of the expansion will be penalized. Penalization techniques have the goal of obtaining a smooth appearance for f, and a technique is to opt for the integrated square second derivative cubic spline penalty.

The criterion to be minimized could be written in the form

$$\sum_i \{y_i - f(x_i)\}^2 + \lambda \int \{f^{''}(x)\}^2 dx$$

and this aims at penalizing rough versions of f, and the result [6] is designed to be a smooth $\widehat{f}$ function.

2.3. Group Specific Smoothers to Visually Display Interactions

The curvilinear trend is displayed in this section for group-specific categories, as determined by antenna type categories. Other factors are also considered in the next sections, such as device type, device status, modulation, and interference type.

The strategy of obtaining smooth functions can be applied for fitting group-specific trends. In this application groups emerge due to the environmental conditions. For each group the association between y and x is allowed to be nonlinear. More generally, the following specification can be considered:

$$E(y|x) = \begin{cases} \mathrm{f}_{\text{Dipole}}(x) & \text{if Antenna type is Dipole} \\ \mathrm{f}_{\text{Directional}}(x) & \text{if Antenna type is Directional} \\ \mathrm{f}_{\text{Omnidirectional}}(x) & \text{if Antenna type is Omnidirectional} \\ \mathrm{f}_{\text{Yagi}}(x) & \text{if Antenna type is Yagi} \end{cases}$$

In the setting described here, there will be four estimators, one estimator for each group. The data used for each estimator corresponds to the data recorded in each group determined by antenna type. Other examples of groups are shown in upcoming sections.

2.4. R Software Implementation

2.4.1. Data

The illustrations presented in this paper deal with the dataset posted online [7]. On the website it was not stated whether the data was simulated or not. Hence, the trends showed in this paper apply only to this particular data.

2.4.2. Visualization Software

There are several statistical techniques for establishing flexible associations observed from datasets. One example is the approach implemented in the R [8] software package `ggplot2` [9]. Data science applications that explore associations among study variables can be addressed by using flexible software [10] implementations.

An example R code is described here for illustration.

```
ggplot(data = data.RF, aes(x=Wind.Speed,y=WiFi.strength,
colour=group))+ stat_smooth(method='gam',
formula=y~s(x,bs ="cr"),se=TRUE)
```

These lines of R code would be modified further in the upcoming sections. In each case results are shown to produce visualization techniques where the outcome of study is y that is allowed to vary non-linearly across different values of the explanatory variable x. Smooth mean function estimators are obtained for each group when the specification `colour=group` is used. The association is modeled using flexible spline smoothing techniques implemented using the generalized additive model when specifying the `method='gam'` argument available in software [9, 10]. The fitting mechanism opted for was regression splines, and this was coded in the R algorithm as `formula=y s(x,bs ="cr")`, where `cr` denotes cubic regression splines. The `bs="cr"` specification indicates that cubic spline basis was implemented for the expansion of the f function. The option `se=TRUE` produces shaded confidence regions in the graphics, and these can be interpreted as uncertainty estimators corresponding to the portrayed association. Smooth estimators were obtained for the different groups. For example, when `color=Antenna.Type` was used, four different estimators were obtained, one for each group of antenna type (dipole, directional, omnidirectional, and yagi). The upcoming sections discuss several such graphical explorations. Several studies reported conditional mean estimators [10] where group specific [10, 11] smooth functions were obtained using the `ggplot` framework.

The trends reported were obtained from the dataset [7] that had 164160 observations available for each feature, including WiFi strength, air pressure, battery level, CPU usage. While this work presents selected illustrations, the strategy could be used for other datasets that recorded this type of information. The implementation details pertain to the statistical environment `R` [8], an open source software for statistical computing where graphics can be generated with specialized statistical visual techniques.

3. Antenna Type

The directional antennas were reported [12] to overcome the drawbacks of omnidirectional antennas. WiFi strength was reported in dBm, and a smaller dBm value indicated a poorer WiFi signal. The R code printed produced Fig. 1, where a smoother was displayed for each group.

```
ggplot(data = data.RF, aes(x=Wind.Speed, y=WiFi.Strength,
colour=Antenna.Type))+stat_smooth(method='gam',
formula=y~s(x,bs="cr"),se=TRUE)
```

In this application the WiFi signal was the response variable, and wind speed in km/hr was the explanatory variable. The group factor was antenna type. The approach shows smooth trends to illustrate the association for each antenna type. There were four types of antennas that appeared in the dataset. Fig. 1 illustrates the observed association between WiFi strength and wind speed for each of the four antenna types. In this illustration, the four antennas types studied display somewhat different patterns of association between WiFi strength and wind speed.

4. Device Type

There were three types of devices used for the study: HackRF, Halow-U, and SteamDeck. Steam Deck technology has been proposed for the construction of robots [13] and has been used for gaming [14]. HackRF has been proposed for GPS [15] systems. Fig. 2 illustrates the observed association between WiFi strength and wind speed for each of the three device types. In this illustration, the three device types studied display somewhat different patterns of association between WiFi strength and wind speed.

The R code printed produced Fig. 2, where a smoother was displayed for each group.

```
ggplot(data = data.RF, aes(x=Wind.Speed, y=WiFi.Strength,
colour=Device.Type))+stat_smooth(method='gam',
formula=y~s(x,bs="cr"),se=TRUE)
```

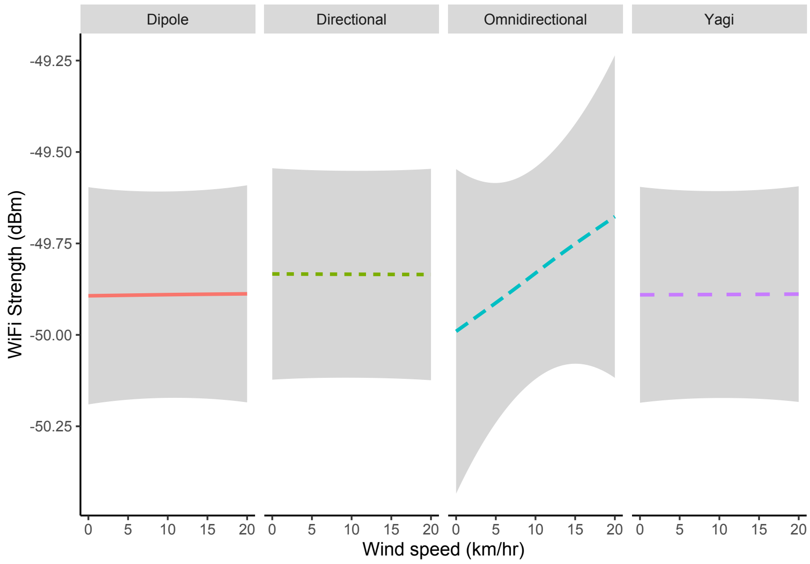

Fig. 1. Graph illustrates the estimated trends for WiFi strength as a function of wind speed for four groups of antenna type: dipole, directional, omnidirectional, and yagi.

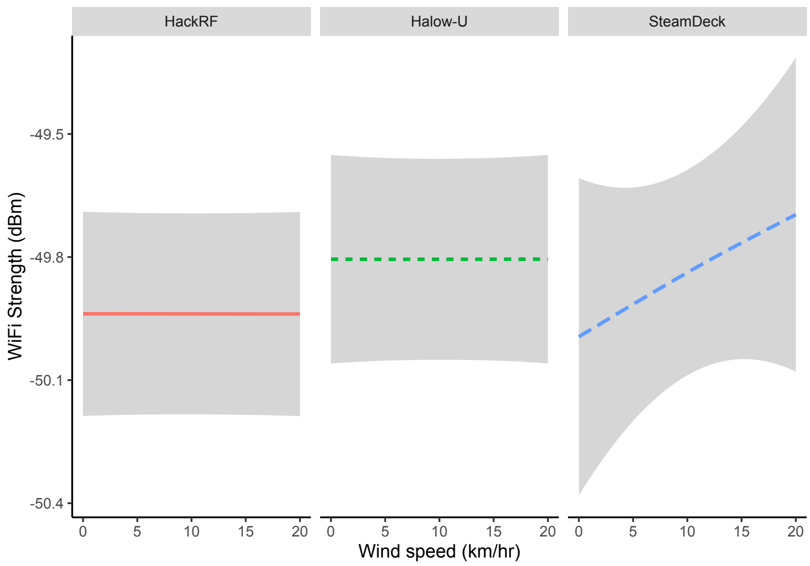

Fig. 2. Graph displays the estimated trends for WiFi strength as a function of wind speed for three cases of device type: HackRF, Halow-U, and SteanDeck.

5. Modulation

There were several types of modulations used for the study: Amplitude Modulation (AM), Frequency Modulation (FM), Quadrature Amplitude Modulation (QAM), Binary Phase Shift

Keying (BPSK), Quadrature - Phase Shift Keying (QPSK), and 8 Phase Shift Keying (8PSK). Humidity refers to the relative humidity at the location of signal observation and reported as percent. Levels of humidity ranged from 20% to 80%. Prior studies have reported on the impact of humidity [16] on RF signals.

Fig.3 illustrates the estimated association between WiFi strength and humidity for each modulation setup. In Fig.3 the QAM modulation shows a pattern that looks somewhat different than for the other modulations.

The R code printed produced Fig. 3, where a smoother was displayed for each group.

```
ggplot(data = data.RF, aes(x=Humidity, y=WiFi.Strength,
colour=Modulation))+stat_smooth(method='gam',
formula=y˜s(x,bs="cr"),se=TRUE)
```

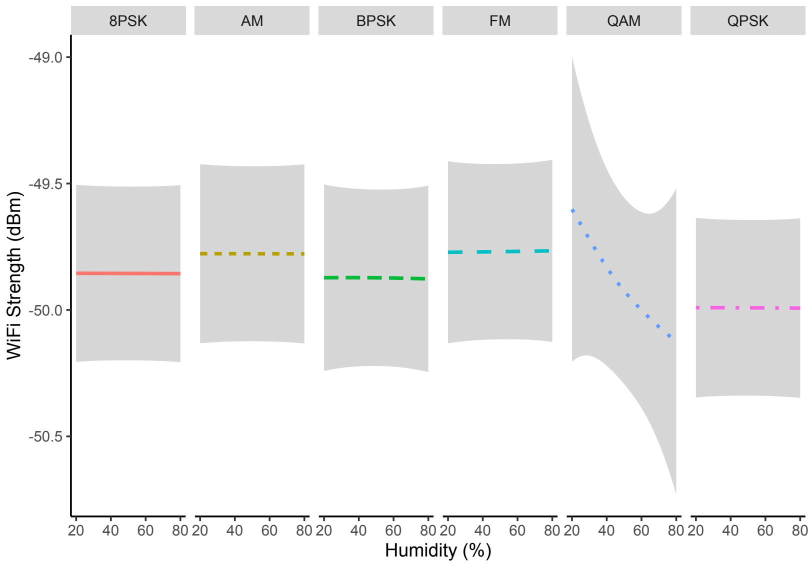

Fig. 3. Graph shows estimated trends for WiFi strength as a function of humidity for six modulation types.

6. Device Status

There were three types of device statuses reported in the dataset: running game, streaming I/Q data, and transmitting beacon signal. Precipitation refers to the amount of precipitation at the location of the signal observation in millimeters (mm). The range of observed precipitation was between 0 to 50 mm. Fig. 4 illustrates the observed association between signal strength and precipitation for each device status.

The R code listed here generated Fig. 4, where a smoother was displayed for each group.

```
ggplot(data = data.RF, aes(x=Precipitation, y=Signal.Strength,
colour=Device.Status))+stat_smooth(method='gam',
formula=y˜s(x,bs="cr"),se=TRUE)
```

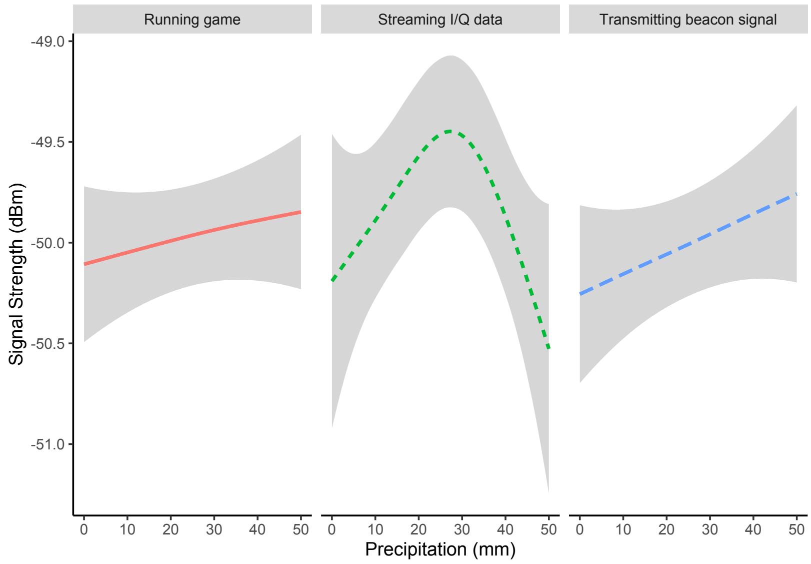

Fig. 4. Graph illustrates estimated trends for signal strength as a function of precipitation for three cases of device status.

When the device streamed I/Q data the signal strength decreased as precipitation increased. When device transmitted beacon signal or ran a game, the signal strength was less variable than when streaming I/Q data.

7. Interference Type

The dataset included the type of interference in the environment. Possible options included none, co-channel, adjacent-channel, and intermodulation. Temperature was measured in degrees Celsius.

The R code printed produced Fig. 5, where a smoother was displayed for each group.

```
ggplot(data = data.RF, aes(x=Temperature, y=Signal.Strength,
colour=Interference.Type))+stat_smooth(method='gam',
formula=y~s(x,bs="cr"),se=TRUE)
```

Fig. 5 illustrates that signal strength was not impacted by temperature across the different interference types.

8. Conclusions

Graphics provide a useful tool to portray visual effects between environmental elements and the RF signal strength. Statistical software contains dedicated modules for addressing specilized visualization techniques. The paper showed instances of monitoring the group-specific trends among multiple surrounding factors for RF signal data. The techniques were used when a large amount of observations of data were available. This gave the possibility of investigating how

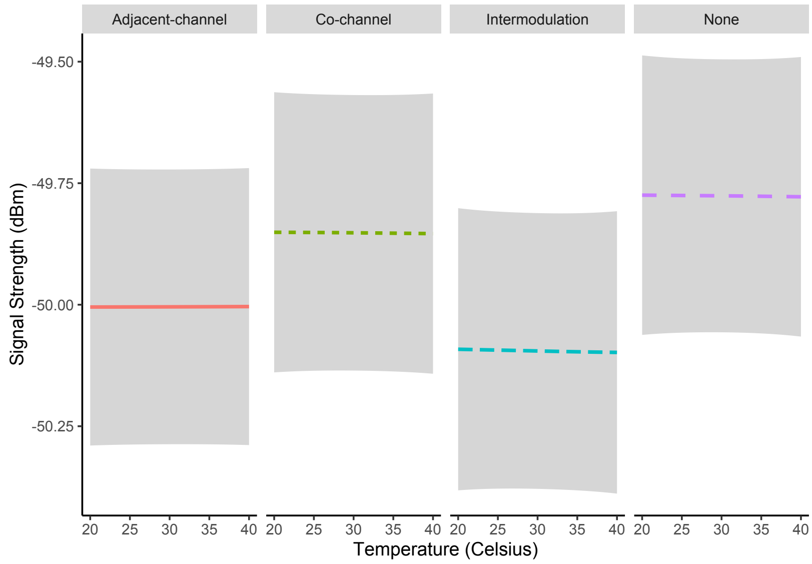

Fig. 5. Graph illustrates estimated trends for signal strength as a function of temperature for four recorded interferences: adjacent channel, co-channel, intermodulation, and no interference.

temperature, wind speed, humidity, and precipitation may impact WiFi and RF signal strength. The approach illustrated provided mean trend estimation as well as uncertainty estimation. The visual tools presented in this paper showed available software and nonlinear modeling strategies based on flexible representations of functions applied to radio frequency signal data.

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