# Exploring the efficacy of Fresnel Zones in the context of fully unobtrusive wireless stress signal detection

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Fig. 1. Stressed [21]

High stress levels can significantly impact an individual's productivity, health, and well-being. In the modern world, stress is a growing concern, and detecting abnormal levels of stress in time can lead to an overall better individual and societal performance while avoiding more serious long-term complications. Given such a significant problem, accurately detecting when a person shows signs of stress can provide essential information for future solutions or scientific advancements. The presence of this sort of information in a company can optimize corporate growth and improve employee satisfaction and efficaciousness. This research focuses on how relevant Fresnel Zones are in the context of unintrusive and unobtrusive stress signal recognition of an individual sitting in an everyday life environment and why such an approach to stress signal detection is worth taking into consideration.

Additional Key Words: Fresnel zones, stress, wireless sensing, activity recognition, unobtrusive sensing, health, productivity, deep learning, CSI

## 1 INTRODUCTION

Everyday life contains unavoidable challenges and burdens, which lead to stress. The sooner abnormal levels of stress are dealt with, the less long-term damage and consequences they pose. Chronic stress in both individuals and in groups of people has negative effects on social and economic levels [10]. Successfully keeping track of such stress can provide great help for individuals, companies, or institutions.

A person under stress shows increased stress hormones, but detecting such changes requires invasive methods, qualified personnel, and complex analysis methods [1]. Leaving convoluted methods to measure stress aside, stress can be measured with various sensors by analyzing changes in body and behavior, such as: body movements, facial cues, pupil diameter, facial blood flow, galvanic skin response, blood pressure, brain activity [1-3,5,9-11,14]. With so many ways to measure stress, some of the questions one should ask itself when choosing one are: Are they reliable? Are they accurate? Is the presence of the means of sensing interfering with the authenticity of the results? A study carried out in 1961 [14] measured pilots' stress by having them wear electroencephalographic sensors that followed how their brains act in different situations. The research conditions were highly obtrusive for the pilots, and subsequently, the results do not accurately mirror those in usual flight operations. [1,14] From this, we can conclude that the more aware people are that they are being monitored, the less authentic the results are. Therefore, WiFi sensing seems to be the best solution to monitor specific activities or states of individuals. With enough effort, such a solution can be implemented seamlessly into a working environment so that no direct user interaction is needed. Privacy is also one of the biggest concerns when collecting user data. Research strongly supports that visual and audio data collection are among the least accepted by the general public [6,12], which is why such sensing methods are not considered throughout the research.

A study [9] proved that body movement could be a reliable stress indicator when measured correctly by having an average error rate as low as 1.36%. Other studies [1,5,11,13] also support the same theory.

Even though plenty of studies show that wireless radar sensing is a good choice for detecting and sensing human actions and activities [4,7,8,15,16], there have been no studies considering using wireless sensing for stress detection.
Whenever the word "wireless" comes into play, Fresnel zones are highly relevant and play a big part in the effectiveness and accuracy of any technology implemented. Therefore, this paper explores just how relevant they are by comparing how well a human's activities can be detected based on their position relative to the WiFi nodes.

## 2 THEORETICAL BACKGROUND

In order to understand what exactly the Fresnel zones are and what sort of importance they possess in the context of activity recognition, a run-through of relevant information needs to be brought up.

### 2.1 THE FRESNEL ZONES

The book chapter [17] defines the Fresnel zones in the following way:
"Considering Tx and Rx are the RF transmitter and receiver, respectively as shown in Fig. 3.1, the Fresnel Zones are formed by confocal ellipsoids with the pair of transceivers located at the two foci. For easy illustration, we only show the 2-dimensional eclipses rather than 3-dimensional ellipsoids. For a given radio wavelength λ, Fresnel Zones containing n ellipsoids can be constructed as follows:

$$|Tx\ Qn| + |Qn\ Rx| - |Tx\ Rx| = n\lambda/2 \quad \text{(F 2.1)}$$

where Qn is a point on the nth ellipse. There are infinite number of Fresnel Zones. The innermost ellipsoid is called the First Fresnel Zone (FFZ), the elliptic annulus between the first and second ellipsoids is called the Second Fresnel Zone, and the nth Fresnel Zone corresponds to the elliptic annulus between the (n − 1)th and nth ellipsoids. The boundary of the nth Fresnel Zone bn is defined as follows:

$$bn = \{Qn, Tx, Rx \mid |Tx\ Qn| + |Qn\ Rx| - |Tx\ Rx| = n\lambda/2\} \quad \text{(F 2.2)}$$

The path length of the signal reflected or diffracted through the nth Fresnel Zone boundary is nλ/2 longer than that of the Line-of-Sight (LoS) path signal."
Since the accuracy of the radio waves used by the CSI node is close to 5cm in the first Fresnel zone, small movements such as a leg bouncing or a hand slightly moving might not be detected. With an increase in the number of the Fresnel zone, an increase in the angle created by Tx, Px and the observed point, and a decrease in distance between zones is present. As a result, increasingly smaller movements should theoretically be increasingly detectable the higher the Fresnel zone is.

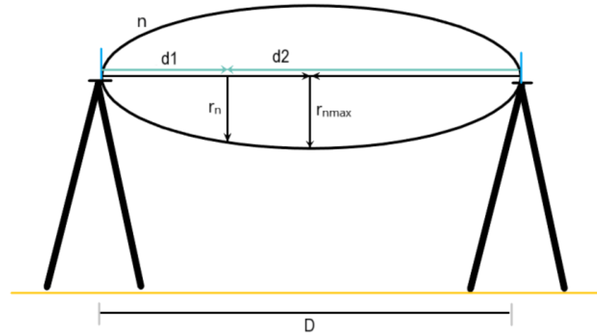


Fig 2.1. Fresnel zones visualisation

### 2.2 CALCULATING FRESNEL ZONE RADIUS

Calculating the radius of a Fresnel Zone is done in the following way [20]:
"The formula for the radius of the n-th Fresnel zone reads:

$$r_n = \sqrt{n * \lambda * d1 * d2 / (d1 + d2)} \quad \text{(F 2.3)}$$

where: λ is the wavelength of the wireless beam transmitted by the antenna; and d1, d2, $r_n$ as in the picture below:
If we want to get the longest Fresnel zone radius ($r_{nmax}$), we have to recall that an ellipsoid is the biggest at its center. That is, when we have d1 = d2 = D / 2, and the above formula simplifies to:

$$r_{nmax} = \sqrt{n * \lambda * D / 4}\text{"} \quad \text{(F 2.4)}$$

## 3 PROBLEM STATEMENT

A survey [1] states the following: "Traditionally, stress has been measured using assessment based on humans rating stress levels on some scale (e.g., Relative Stress Scale, Fear Survey Schedule, Cook Medley Hostility Scale, and Brief Symptom Inventory), which are subjective. All these assessments require major human intervention, including manually recognizing and interpreting visual patterns (possibly with some support tools) of behavior in observational studies. Stress experiments that use various sensors to obtain objective measures of stress also use subjective assessment to verify measurements obtained from sensors". Wireless stress sensing can open a whole new perspective to ubiquitous, non-invasive, unobtrusive, and universal well-being monitoring.
Fresnel zones are an old and solid concept, but there is little to no research made about how the detection of certain activities varies based on them.
Since there appears to be a clear gap in research about stress recognition using wireless sensors and how Fresnel zones might or might not affect such an approach, this research document aims to add some clarity to these topics.

## 4 RESEARCH QUESTIONS

The main objective of this research paper is to provide some clarity related to the following questions:

- Is wireless sensing a good and reliable approach for stress signal detection of an individual sitting, and is there reason to conduct further research on the topic? (RQ 1)
  - Is the detection accuracy at least 70%, so that implementing a wireless stress monitor can at least be considered? (RQ 1.1)
  - Considering the results of the sub-question above, would such a wireless stress monitor provide proper advantages over already existing stress monitor solutions? (RQ 1.2)

- Does the difference in Fresnel zones significantly impact the overall performance of stress signal detection? (RQ 2)
  - Does the system perform as expected and has a better (or equal) performance when the subject is positioned farther than the 50th Fresnel zone compared to when it is placed in the 1st? (RQ 2.1)

## 5 RELATED WORKS

Wi-Motion [4] has been used in order to successfully recognize human activities (bend, halve squat, step, stretch leg, jump) with similar radio technology and got promising results: 96.6% accuracy in LOS (line-of-sight) environment and 92% accuracy in NLOS (non-line-of-sight) environment.

By using the same NLOS radio sensing technology as this research, researchers managed to get an accuracy between 75% and 85% for recognizing proper hygiene measures of individuals while taking a shower [16]. Other research [4,7,8] also shows that activity and action recognition through radar sensing is indeed effective and can provide results with an accuracy as high as 96%.

Another research [5,9] supports that people under stress show higher signs of discomfort, which impact body movement levels and drinking water frequency, among other things.

One study [11] managed to obtain an accuracy of 83% for stress recognition in people with desk jobs. However, it did so by having the participants wear a Fitbit® that monitored them throughout the day and night, and by using an app called LaborCheck, which monitored their full use of the computer. Such methods can provide excellent results during research but pose a privacy concern in everyday life situations.

Various studies state that the heart rate accurately measures stress, especially its variability [1,3,5,10,11,15]. It should be noted that the WiFi channel state information sensors can sense heart rate variability [15], so future research can aim to implement such a technique in order to achieve a possibly better system.

A chapter in the book "Contactless Human Activity Analysis" [17] explores Fresnel zones and already existing studies about them. There have been studies that successfully managed to track respiration [18] and finger drawing [19] by taking Fresnel zones into account. However, no study made an actual comparison in order to determine their importance.

## 6 THE EXPERIMENT

The experiment consists of having test subjects repeatedly do certain stress-related activities at different distances from the CSI nodes to gather the movement's channel state information (CSI) and train an Artificial Intelligence (AI) algorithm to detect when such activities happen.

### 6.1 THE EXPERIMENT ENVIRONMENT


Fig. 6.1. The experiment environment

The experiment took place inside an office [Fig 6.1] in which the transmitter node T and receiver node R were placed at four different positions (Px), which are set at increments of 50cm from the subject line S, starting from 0: P0, P60, P120, P180 (the first position is on the subject line). For a distance of x centimeters between the nodes T;R and S, the transmitter is placed at the intersection of line VR with Px and the receiver is placed at the intersection of line VL with Px.

The length of S and all Px is of 220cm.

When setting up the environment, the following goals were taken into consideration:

- The whole testing setup with four different node positions should fit in the office.
- No obstructions should be present in the testing area during the data gathering. Any interference from the outside or trial error results in the restart of the data gathering for the activity.
- One of the distances should be at least long enough so that the distance between Fresnel zones is under 1cm at the position of the test subject. Since that starts to happen around the 50th Fresnel Zone, so 50 is the lower limit for at least one of the positions. P180 should have the subject in the 105th Fresnel Zone. (F 2.4)
- Because of the high interference the metal in the available desks would have with the results, the decision to have the test subjects rest on their knees instead of a desk has been made

### 6.2 HARDWARE SETUP USED

The primary means of transmitting, receiving, and collecting the CSI data are two GIGABYTE GB-EACE-3450 ultra-compact PCs equipped with 3 WiFi antennas through which radio signals are transmitted and received. After performing the experiment, it has been concluded that only 2 out of the 3 antennas did actually work, hence the 100x60 instead of 100x90 data frames illustrated in the next chapter. (Fig 7.1)

### 6.3 DATA GATHERING PLAN

The gathering of the data has been done by having 12 volunteers act as test subjects and perform the following tasks:

- Move from a comfortable position in which they are resting their back on the chair to a position in which they are bending forward on their knees, after which they return to the initial position. The subject changes position every 5 seconds and performs each series of movements for a total of 10 times, accounting to 100 seconds in total.
- Shake one of their legs for 10 seconds, after which they rest for 10 seconds in a neutral sitting position. This series of shaking and resting is repeated 5 times for each leg individually, summing up to 100 seconds per leg. During the 10 seconds of rest, the data for the neutral activity will be gathered.
- Lean from one armrest of the chair to the other one. This movement is repeated every 5 seconds for 20 times, adding up to 100 seconds.

## 7 METHODOLOGY

This chapter encapsulates the process through which the data collected with the setup presented in Chapter 6 has yielded the results in Chapter 8.

### 7.1 DATA COLLECTION AND PREPROCESSING

The data has been collected by having the receiving node R record the incoming radio transmitted packets from the transmitter node T while each experiment in the data gathering plan above was being carried out. The received data has then been stored in the node R, together with the timestamps of each packet. The sampling rate of the wireless packets transmitted was of 100Hz, and the wavelength was of 5.3GHz.

The preprocessing of the collected data consisted in turning the files with raw CSV data into datasets in .h5py format so that the collected data can be further processed in python to create images that can be used to train a classifier.

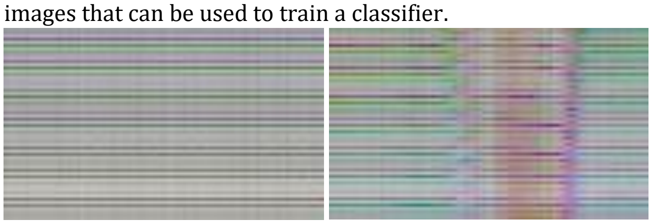

Fig. 7.1. One second of data classified as neutral (left) and armrest (right)

After further preprocessing of the data, the images above (Fig 7.1) have been created as a way to represent one second of data collection. Their size is 100x60, which represents data collected over the sampling rate of 100Hz and the 60 subcarriers (2 antennas X 30 subcarriers each)

### 7.2 UNEXPECTED VARIABILITY IN SAMPLING RATE

Once the data had been collected and analyzed, it was obvious that the true sampling rate had very high variability, ranging from 82 to 10079 packets collected in the timeslot of 100 seconds for one activity performed by one test subject. As a resolution to this unexpected issue with data gathering, in which the data can still be usable, every 100 packets received have been modeled as one second.

The position most affected by this variability has been P100, which is why it will be considered less relevant in the results and conclusions sections. (Fig 7.2)

| | **Images created / activity** | | | | |
|---|---|---|---|---|---|
| **Position** | Armr | Desk | L leg | R leg | Neutral |
| **P0** | 182 | 289 | 131 | 139 | 269 |
| **P60** | 161 | 160 | 43 | 83 | 123 |
| **P120** | 33 | 23 | 4 | 6 | 11 |
| **P180** | 112 | 76 | 22 | 13 | 36 |

Fig 7.2. Images computed per activity based on position

### 7.3 AI CLASSIFIER IMPLEMENTATION

The classifying model has been implemented using convolutional neural networks (CNNs). In order to avoid bias in the results due to not diversifying the testing, training and validation sets enough, Stratified K-fold cross-validation has been used. The collected data from each position has been used three different times with a 5-split Stratified K-fold cross-validation, resulting in 15 different results for each position tested. A visual representation of how the Stratified K-fold cross-validation was used can be found below in Fig. 7.3:

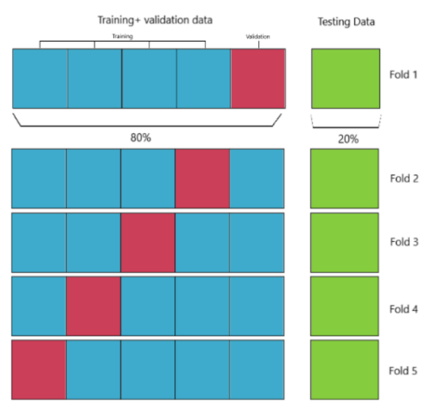


Fig. 7.3. Stratified K-fold cross-validation

Such an approach to testing the results was necessary due to the black box design of CNNs since the feature extraction and bias related to one data split can not be predicted.

For each fold, the history and confusion matrix resulting from using the model on the testing set have been stored as means to process the results of the study.

## 8 RESULTS

After gathering all the results from the experiment in chapter 6, relevant plots have been created in the next subchapters to represent the results and aid in achieving a relevant conclusion. The orange dot present in each box plot entry is the position of the mean.
The accuracies and F1 scores were achieved by using the following formulas based on the confusion matrix:

Accuracy = Diagonal Sum / All elements sum

F1 Score* = (2 * Precision * Recall) / (Precision + Recall)

### 8.1 ACCURACY OVER TIME

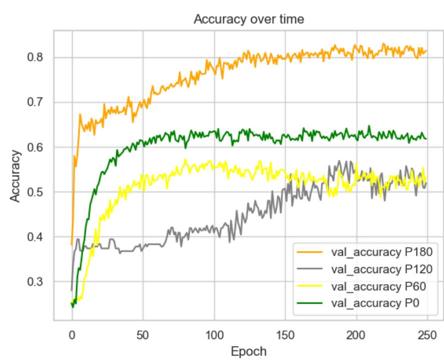


Fig 8.1. Accuracy over time

By analyzing the table above (Fig 8.1), which plots the accuracy over each epoch of the classifying algorithm, clear dominance in accuracy can be observed for P180 over the whole duration of creating the model. As expected, P120 performs the lowest, but it ends up with the same accuracy as P120 towards the final epoch.

### 8.2 ACCURACY BASED ON POSITION

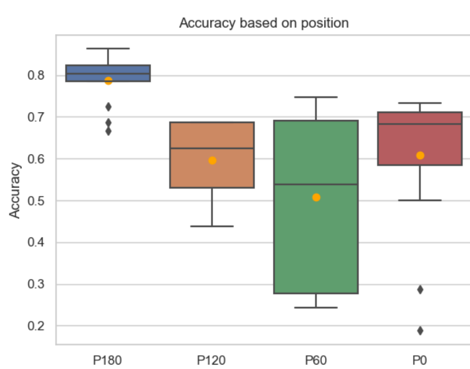


Fig 8.2. Accuracy based on position

In the first plot [Fig 8.1] the accuracy has been evaluated based on the validation set, while in the one above (Fig 8.2), the confusion matrix resulting from testing the model on the test set has been used. As can be observed, clear dominance in accuracy for P180 is also present in this plot, with an average accuracy of 80%.

### 8.3 OVERALL F1 SCORES

*F1 scores with 0 true positive values have been disregarded while creating the plots due to the small sample size of the experiment. A plot of the F1 scores without this tweak is present in Chapter 10.

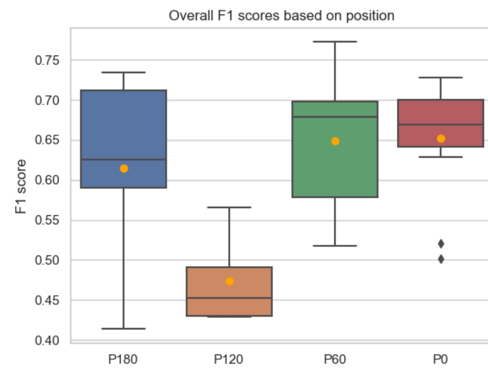


Fig. 8.3. Overall F1 scores based on position

Since accuracy is not decisive by itself when comparing classifiers, F1 scores have been computed as well. Compared to the accuracy plots, the plot above (Fig 8.3) offers a completely different perspective on the performance of the classifiers trained in each position. The F1 scores of P60 and P120 average around 65%, while the ones for P180 average around 62%.

### 8.4 F1 SCORES BASED ON LABEL

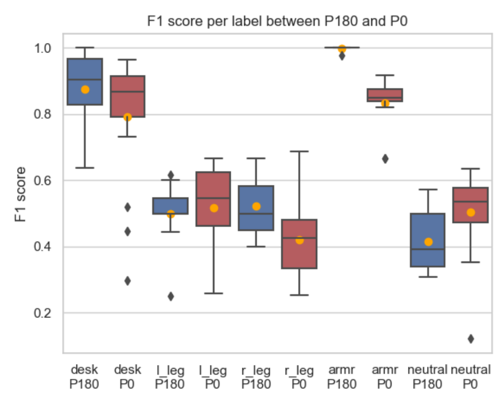


Fig. 8.4. F1 score per label between P180 and P0

Since the previous plot (Fig 8.3) shows a higher overall F1 score for P0 and P60 while being compared to P180, the plot above (Fig 8.4) compares the scores per label so that a more in-depth analysis and understanding can be achieved. If the amount of training and testing data is taken into consideration (Fig 7.2), it becomes clear that P180 only underperforms for labels that had a low sample size (l_leg, r_leg, neutral), and outperforms for the labels that had a reasonable amount (desk, armr).

## 9 CONCLUSIONS

After considering all the results and testing conditions presented in the previous chapters, the following conclusions can be made in an attempt to answer the research questions in chapter 4:

Based on the accuracy, the model of the setup placed in P180 performs well (Fig 8.1, 8.2) by scoring an accuracy of around 80%. All the other positions tested scored lower than 70%, with accuracy lower than the lower bound proposed to decide whether the model is reasonably accurate. (RQ 1.1)

As stated before, the results present in this paper show reasonably high stress signal detection in the setup P180, even with a very small sample size. What should be noted though, is that successfully detecting a stress signal does not result in actual stress being present in the observed subject. If we would assume that the stress signal detection efficiency would be the same as the one for actually detecting whether stress is present, then the performance of the solution for stress detection would be about average while compared to other means of sensing present in Chapter 5. (RQ 1.2)

Because of the unfavorable research conditions (small sample size and imbalanced data), concluding whether wireless sensing for stress detection is good and reliable is not possible. On the contrary, the results of the experiment proved to be encouraging enough for future research on the topic to be relevant. A follow-up research with an exponentially higher sample size and that could conclude how well actual stress can be computed via wireless CSI sensing would provide further clarity and more concrete evidence to support or deny the usage of wireless CSI sensors in the context of stress detection. (RQ 1)

The increased accuracy present in Fig 8.1 and 8.2 for P180 supports the claim that a subject performing a stress related motion will be more accurately sensed when placed in a higher Fresnel zone in the context of wireless CSI activity recognition. Even though the lower accuracy for P60 in contrast to P0 could be due to the reduced sample size in training the classifiers, it contradicts the increase in accuracy being directly proportional to the increase in the Fresnel zone. Contrary to the accuracy plots, Fig 8.3 shows a lower F1 score for P180, which showcases the high degree of imbalanced data used to train the models. Chapter 8.4 supports the claim that the F1 score of P180 would be higher if equally sized sample data had been provided to both the classifiers for P180 and P0.

While the observed results point towards claiming that the system performs better when the subject is placed in a high Fresnel zone in comparison to the 1st one, the small sample data and imbalanced dataset prevent a concrete conclusion on the matter. (RQ 2.1)

As discussed in the conclusion to RQ 2.1, the observed results point towards claiming that Fresnel zones have a noticeable impact on the overall performance of stress signal detection. The imbalance in the accuracies and data used to create the classifiers make this claim inconclusive though. A follow-up research with a higher number of participants and a balanced dataset can succeed in transposing this claim into a fact. (RQ 2)

## 10 LIMITATIONS AND FUTURE WORK

As stated throughout the paper, the main limitations that this research faced and should be improved in future works are the following:

- Very high data inconsistency due to unreliable processing units. The nodes mentioned in chapter 6.2 were old and would sometimes overheat, event which limited the receiving/transmission rate. The collected files should be checked constantly for consistency in future works in order to avoid such inconsistency. Because of the very small sample size presented in Fig 7.2, which was used to train the classifier, the F1 Scores in Fig. 8.3 and 8.4 do not hold as much weight as they should in deciding a conclusion. A boxplot with the F1 scores if all the NaN values were considered to be 0 is present at the end of the chapter (Fig 10.1).
- The test subject sample was small. Data gathered from 12 individuals might be biased and yield unreliable results. A subject test sample of at least 30 should greatly reduce the possible bias.
- The movements recognized by the classifier are only signals that could lead to stress. The focus of the research was gathering enough data to support the relevance of future research about wireless stress detection through CSI. Future research should be conducted to decide what movements are the most appropriate for stress detection and how to compute genuine stress presence with their aid.

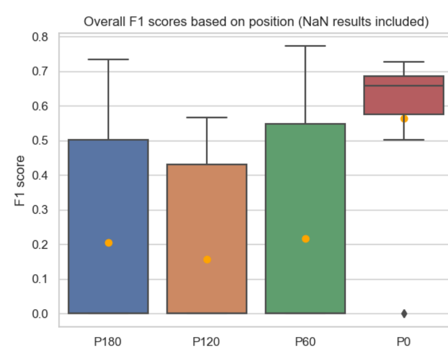


Fig. 10.1. Overall F1 scores if NaN values are interpreted as 0

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