Characterization of Smart Phone Received Signal Strength Indication for WLAN Indoor Positioning Accuracy Improvement

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Abstract—Considering that indoor positioning applications based on wireless local area network location fingerprinting would be mainly used on the mobile devices. This paper investigates the differences of received signal strength indication (RSSI) between different smart phones and the distributions of RSSI are also analyzed. The statistical analysis of experimental results shows the differences of RSSI between different smart phones are not trivial. Nearly 65% of the RSSI histograms are significantly peaked relative to Gaussian distribution and 65% of them are left-skewed distribution. Therefore, taking skewness and kurtosis coefficients into account, Gaussian distribution is not sufficient to ensure an accurate modeling of the RSSI. The impacts of human behavior on RSSI distribution are explored and two types of human behavior are revealed to be the cause of bi-modal distribution. The statistical data analysis could enable smart phone indoor positioning systems designers to improve positioning performance and to model location fingerprinting based indoor positioning systems.

Index Terms—WLAN; RSSI; Indoor Positioning; Skewness Coefficient; Kurtosis Coefficient

I. INTRODUCTION

The broad smart phone market and location based services lead to a widespread demand for mobile phone positioning systems with relatively high accuracy. Although the Global Navigation Satellite System (GNSS) can suffice positioning services in most cases, it suffers in indoor environments because its signal decays rapidly when passing through the wall [1]. As an alternative or complementary solution for indoor environments, Bahl et al. [2] suggested a positioning approach based on the received signal strength indication (RSSI) in wireless local area network (WLAN) networks. Nowadays, the WLAN positioning becomes more and more attractive for indoor positioning because of the increasing availability of public and private network Access Point (APs) [3].

Positioning systems that fit for the large-scale urban application such as metropolitan-scale positioning should be adaptable to a variety of mobile phones with similar positioning accuracy. The critical issue that affects the RSSI based positioning accuracy is the adaptability of RSSI fingerprint database establishment for various smart phones. The positioning accuracy of a smart phone depends on the comparison between the offline RSSI fingerprint database and the collected online real-time RSSI data. If the online real-time RSSI data collected by different smart phones differs to some extent, the position accuracy differs too, which means that the positioning system is not stable or reliable. Currently, there are only a few types of terminals that can be used to collect and establish the offline RSSI fingerprint database. However, there are millions of users with massive different kinds of smart phones and there will be more different smart phones coming to the market every day. Thus, it is impractical to establish the offline RSSI fingerprint database that covers all kinds of smart phones. Therefore, the variations in the RSSI data of different devices should be taken full consideration for a commercial indoor positioning system that is designed for megacity urban application.

The understanding of the RSSI data is essential for location determination algorithms such as the probabilistic approach [4–6]. The Gaussian or log-normal distribution is currently used to model the randomness of RSSI. However, the large-scale measurements in [5] revealed that the majority of RSSI histograms fitted very well with Gaussian distribution and there were a few histograms that could fit better with bi-modal Gaussian distributions. On the other hand, most existing data were collected by laptops. Compared with laptops, the smart phones are smaller and their computing power is very limited, thus the smart phones would be more sensitive to the environmental change when collecting the RSSI for indoor positioning application. This is clearly supported by measurement results in section 3. This has motivated our current study in characterizing RSSI for WLAN based indoor positioning accuracy and the most popular smart phones - Android mobile phones were selected in the experiments.

By comparing the histograms of RSSI collected in user’s presence/absence scenarios, an evaluation of the effect of user’s presence/absence on RSSI was reported by Kaemarungsi in [7]. The range of RSSI was wider and the standard deviation was also increased when user was present. These previous study indicated that the human behaviors in the measurement environment could influence the RSSI distribution. However, the human behaviors in the measurement are rather complex and
they cannot be simply summarized in two scenarios: presence/absence. On the other hand, the bi-modal distribution was observed in [5, 8], but the cause of bi-modal distribution had never been revealed. In our current work, the human behaviors in the measurement environment are organized into four categories: absence, sitting/standing still, moving randomly and moving specifically.

In this paper, the RSSI data collected by Android smart phones are analyzed. From the collected data, hardware diversity impacts on the RSSI value are discussed. In addition, the distribution of RSSI data is analyzed and characterized by assessing the skewness coefficient and kurtosis coefficient. A comprehensive evaluation on the impacts of human behaviors on the distribution of WLAN RSSI is made and the cause of bi-modal distribution is also investigated. The outcomes of this paper could provide theoretical support for indoor positioning technology.

The paper consists of five sections. Following this brief introduction, Section 2 describes the measurement setup and data collection. Section 3 explores the effect of different smart phones on RSSI. The distribution of the RSSI data and the impacts of human behavior are discussed in Section 4. Finally, Section 5 concludes the paper.

II. EXPERIMENTAL SETUP AND MEASUREMENT

The precision measurements of the WLAN RSSI are investigated using Android smart phones. Four Android smart phones, namely HTC G7, HTC T328, Samsung I9100 and Samsung S7568, equipped with custom RSSI collecting application software, were used to collect samples of RSSI data from APs at the Guidance, Navigation and Control (GNC) Lab in the School of Aeronautics and Astronautics of Shanghai Jiao Tong University. The dimension of GNC lab is approximately 23m x 7m (with Room 2221 nearly 6m x 5m, Room 2220 nearly 6m x 5m, 2219 nearly 12m x 5m). Six wireless APs located at height of 2.2m above the floor were deployed in GNC lab as shown in Fig. 1. The six APs have the same vendors and models (Netgear-WGR614V10). As shown in Fig. 1, a small area is defined as a grid of 25 points (the solid dots in Fig. 1) with 15 in Room 2221 and 10 in the corridor. The minimum distance between two locations called grid spacing was fixed at one meter.

Firstly, measurement was made to detect the differences of RSSI data collected by different smart phones at different APs. Five measurement places as shown in Fig. 1 denoted as L1, L2, L3, L4 and L5 were chosen to collect the RSSI data.

In the experiment, the four smart phones were placed together on a 1.1-meter high tripod. The placement of the four smart phones is shown in Fig. 2. The purpose of this arrangement is to measure the difference of RSSI value collected by four smart phones at the same time and at the same location. Table 1 shows the basic configuration of four Android mobile phones.

Table 1. BASIC CONFIGURATION OF FOUR ANDROID MOBILE PHONES

<table>
<thead>
<tr>
<th>Configuration</th>
<th>Samsung I9100</th>
<th>Samsung S7568</th>
<th>HTC T328</th>
<th>HTC G7</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPU</td>
<td>Exynos 4210</td>
<td>Snapdragon MSM7227 A</td>
<td>Snapdragon MSM7227 A</td>
<td>Snapdragon QSD8250</td>
</tr>
<tr>
<td>Operating System</td>
<td>Android OS 2.3</td>
<td>Android OS 4.0</td>
<td>Android OS 4.0</td>
<td>Android OS 2.2</td>
</tr>
<tr>
<td>Wi-Fi Module</td>
<td>Samsung SWB-B23</td>
<td>unknown</td>
<td>Broadcom BCM4329</td>
<td>Broadcom BCM4329</td>
</tr>
</tbody>
</table>

Secondly, 2400 samples of the RSSI data were collected at 25 grid locations for a period of 10 minutes at a frequency of 4 Hz using HTC G7 and the distribution of the RSSI data was calculated.

III. DIFFERENCES OF DIVERSITY SMART PHONES

The studies of [9-11] suggested that the location fingerprints with different devices could be different. Intuitively, the RSSI measured by different smart phones should have different results. To examine the influence of hardware on the RSSI data collection, the statistic characteristics of the RSSI data collected by different mobile phones were analyzed. The real received signal energy is a continuous quantity and measured in dBm or decibel milliwatt, while in practical terms, the RSSI is reported in dBm as an integer number [14]. Different devices have their own shifting mechanism to convert the real received signal energy to RSSI value in dBm.

Table 2 lists the manufacturer, phone model, maximum RSSI, minimum RSSI, and the variation range of RSSI for all the Smart phones used in comparison of this section. The maximum measurement value was obtained when placing the smart phones next to the access point, while the minimum measurement value was obtained when placing the smart phones as far as possible from the same access point in the Lab. The variation range of RSSI...
indicated here might not be accurate because it is possible that some RSSI values in dBm will never be received by the software device driver.

As shown in Table 3, the variation range of RSSI data collected by Samsung GTS7568 appears greater than others. This means it can measure the signal with higher resolution and see more variation of signal. On the other hand, the HTC T328 has the shortest range. Consequently, a number of actual measured signal levels may be mapped into the same RSSI value (integer) and it can detect less signal variation. For position fingerprinting purposes, smart phones with a wider range of the RSSI values or better granularity are better as it allows a positioning system to better differentiate between two locations.

### TABLE II. MIN, MAX AND VARIATION RANGE OF RSSI COLLECTED BY DIFFERENT SMART PHONES

<table>
<thead>
<tr>
<th>Manufacturer</th>
<th>Phone Model</th>
<th>MIN (dBm)</th>
<th>MAX (dBm)</th>
<th>Range (dBm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Samsung</td>
<td>GTS7568</td>
<td>-93</td>
<td>-3</td>
<td>80</td>
</tr>
<tr>
<td>Samsung</td>
<td>I900</td>
<td>-95</td>
<td>-24</td>
<td>71</td>
</tr>
<tr>
<td>HTC</td>
<td>G7</td>
<td>-96</td>
<td>-35</td>
<td>61</td>
</tr>
<tr>
<td>HTC</td>
<td>T328</td>
<td>-97</td>
<td>-38</td>
<td>59</td>
</tr>
</tbody>
</table>

![Figure 3](image3.png)

**Figure 3.** Mean RSSI of six APs collected by four smart phones at five places.

The RSSI data collected by different mobile phones is shown in Fig. 3. The RSSI differs generally and sometimes the difference can be as high as 25 dBm, even at the same location and at the same time. The average differences of RSSI between two smart phones are listed in the Table 3. It shows the average differences of RSSI between two smart phones are proportional to their differences on the variation range of RSSI data. The larger the differences on the variation ranges of RSSI are, the larger the average of difference of RSSI values could be. Therefore, the location accuracy would decrease significantly if the variation ranges of RSSI data belong to the smart phones on offline phase and online phase differs much large. The experimental results in [9] indicated the differences of RSSI between laptops were about 1-2 dBm. However, the RSSI of smart phones in our experiments shows much large differences, e.g., the average differences of RSSI between GTS7568 and the HTC T328 are 8.1 dBm.

### TABLE III. THE AVERAGE DIFFERENCES (IN DBM) OF RSSI VALUE BETWEEN FOUR SMART PHONES BEFORE CALIBRATION

<table>
<thead>
<tr>
<th>Manufacturer</th>
<th>Phone Model</th>
<th>MIN (dBm)</th>
<th>MAX (dBm)</th>
<th>Range (dBm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Samsung GTS7568</td>
<td>I900</td>
<td>0</td>
<td>6.98</td>
<td>7.76</td>
</tr>
<tr>
<td>HTC G7</td>
<td>T328</td>
<td>7.76</td>
<td>4.72</td>
<td>2.60</td>
</tr>
</tbody>
</table>

![Figure 4](image4.png)

**Figure 4.** The standard deviation of six AP’s RSSI collected by different mobile phones.

As shown by the measurement results, the RSSI data collected by different Android smart phones differs and sometimes substantially. The offline RSSI fingerprint database consists of the mean of RSSI data or the mean combined standard deviation of RSSI data in generally, while the online RSSI data usually consists of the mean of RSSI data. The substantial difference between RSSI collected by offline device and online device would result in tremendous positioning error. Therefore, it is essential to calibrate the RSSI to adjust the difference and it is also the mainly work of our team in the future.

### IV. DISTRIBUTION OF RSSI

Existing works [5, 12] used the Gaussian or log-normal distribution that was symmetric or right-skewed to model the randomness of RSSI. Haeberlen in [5] use the Gaussian distribution to modeling RSSI value with parameters (µ, δ) where µ is the mean of RSSI samples, δ is the standard deviation of RSSI samples. However, Haeberlen in [5] claimed an ambiguous conclusion: ‘Most of the intensity histograms were very close to Gaussian’, but the details of the assessment criteria were not reported. On the contrary, the experimental results in [9] indicated that the distribution or histogram of the RSSI have a long tail to the left, which is called left-skewed distribution, if the average RSSI is high (−80 dBm or above). If the average RSSI is low (below −80 dBm).
dBm), the distribution will be almost symmetric or appear to be a log-normal distribution (normal in dB) without the long tail. Obviously, there are some conflicting conclusions regarding the RSSI distribution.

A. Skewness and Kurtosis Coefficient of RSSI

In the current work, six APs (as shown in Fig.1) RSSI data collected by the HTC G7 at 25 grid points as designed in Section 2 were analyzed as well as the distribution of the RSSI data. Although 2400 samples were collected at each grid point, the numbers of RSSI values were limited and in most cases the numbers of RSSI values were below 10 and above 4.

In this subsection, skewness and kurtosis coefficients are used to roughly assess whether the RSSI data obeys the Gaussian distribution. The skewness is a measure of symmetry of data. It is reported by number in which a negative number respects a left-skewed distribution and a positive number respects a right skewed distribution [13]. Kurtosis coefficient is a measure of whether the data are peaked or flat relative to a normal distribution. That is, data sets with high kurtosis coefficient tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. Data sets with low kurtosis coefficient tend to have a flat top near the mean rather than a sharp peak. A uniform distribution would be the extreme case. These descriptive statistical parameters can provide additional insight into the possible distribution of the RSSI in addition to the mean and standard deviation values. For univariate data $X = \{x_1, x_2, \ldots, x_n\}$ with the mean $\bar{x}$ and standard deviation $\sigma$, skewness $s$ and kurtosis coefficient $k$ are defined as follow:

$$s = \frac{\sum (x_i - \bar{x})^3}{(n-1)\sigma^3}$$  \hspace{1cm} (1)

$$k = \frac{\sum (x_i - \bar{x})^4}{(n-1)\sigma^4}$$  \hspace{1cm} (2)

If the univariate data $X$ obeys normal distribution, namely $X \sim N(\bar{x}, \sigma^2)$, skewness $s$ and kurtosis coefficient $k$ also obey normal distribution. The parameter $n$ in our experiments is 2400.

$$s \sim N \left(0, \frac{6(n-2)}{(n+1)(n+3)} \right)$$

$$k \sim N \left(3 - \frac{6}{(n+1)} \frac{24n(n-2)(n-3)}{(n+1)(n+3)(n+5)} \right)$$

Typically, the skewness and kurtosis coefficients of normally distributed variables are 0 and 3 separately. If an absolute value of skewness (kurtosis) coefficient is larger than two standard errors of skewness (kurtosis) coefficient, the data set is considered to be significantly skewed. As the RSSI data is converted into an integer number, a relatively rough assessment criterion is chosen to assess the distribution of RSSI. Here, 0.5 and 1 are chosen as a tolerated bias threshold to the skewness and kurtosis coefficients of normally distributed data.

Fig. 5 and Fig. 6 show the comparisons between skewness and kurtosis coefficients of 6 AP’s RSSI data from 25 locations. Intuitively, Fig. 5 shows that lots of the skewness coefficients are not between -0.5 and 0.5. From Fig. 6, the kurtosis coefficients also distribute loosely around 3. Table 4 and Table 5 show more details about the statistical analysis of the skewness and kurtosis coefficients.

Table 4 lists the distribution of 150 of skewness coefficients. Nearly 65.33% of the skewness coefficients are negative, which means 65% of the histograms are left-skewed. In addition, almost 68% of the skewness are smaller than -0.5 or larger than 0.5, which means that 68% of the histograms are significantly skewed and not symmetrical.

![Figure 5](image1.png)  \hspace{1cm} Figure 5. The skewness of six AP’s RSSI from 25 locations

![Figure 6](image2.png)  \hspace{1cm} Figure 6. The kurtosis of six AP’s RSSI from 25 locations

### Table IV. 150 Skewness Coefficients Distributions

<table>
<thead>
<tr>
<th>Percentage</th>
<th>$s&lt;-0.5$</th>
<th>$-0.5&lt;s&lt;0$</th>
<th>$0&lt;s&lt;0.5$</th>
<th>$s&gt;0.5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>40%</td>
<td>24.67%</td>
<td>25.33%</td>
<td>18%</td>
<td>16.67%</td>
</tr>
</tbody>
</table>

### Table V. 150 Kurtosis Coefficients Distributions

<table>
<thead>
<tr>
<th>Percentage</th>
<th>$k&lt;2$</th>
<th>$2&lt;k&lt;4$</th>
<th>$4&lt;k&lt;9$</th>
<th>$k&gt;9$</th>
</tr>
</thead>
<tbody>
<tr>
<td>6%</td>
<td>34.67%</td>
<td>34.67%</td>
<td>24.67%</td>
<td></td>
</tr>
</tbody>
</table>
histograms are significantly peaked relative to a normal distribution.

Finally, Fig. 7 shows representative samples of the kurtosis coefficient $k$ and the Gaussian curving fitting for the RSSI histograms. Fig. 7-a, 7-b, 7-c and 7-d depict the difference between the relationships of kurtosis and RSSI distribution. When kurtosis coefficient $k$ is nearly 3, the RSSI histogram is close to a Gaussian distribution. However, when $k$ is greater than 4 or less than 2, the RSSI histogram is hardly fitted by the Gaussian distribution. Unfortunately, 65.33% of the kurtosis coefficients are not within the range for a Gaussian distribution. To make it worse, there are nearly 25% of them are bigger than 9. Therefore, the standard Gaussian distribution should be adjusted to fit the RSSI distribution properly.

There are several ways to adjust the Gaussian distribution, depending on the characteristics of the RSSI distribution. If the kurtosis coefficient $k$ is greater than 4, the RSSI data is mainly distributed near the mean of RSSI. In the same way, the smaller the standard deviation $\sigma_s$ is, the RSSI data are more concentrated near the mean value of RSSI. Therefore, if the standard deviation $\sigma_s$ is adjusted by the kurtosis coefficient, such as $\bar{\sigma}_s = \sqrt{\frac{3}{k}} \sigma_s$, the Gaussian curving fitting would be more accurate. Fig. 7 shows the adjusted Gaussian curving fitting (dashed line). Obviously, adjusting the standard deviation with the kurtosis coefficient makes a better fit.

The bi-modal phenomena appear in our experiments as shown in Figure 8, which was also observed in [7, 13]. Fortunately, only 10 of 150 RSSI histograms appear double peaks. In this case, using Gaussian distribution to model the RSSI histogram is not appropriate.

B. Impacts of Human Behaviour

To make sure the measurement environment were under control, RSSI data of AP1 and AP2 were collected at a fixed place P (as shown in Fig. 9) in Room 2221 from four experiment scenarios with human absence, sitting/standing still, moving randomly and moving specifically.

Five groups of RSSI data were collected by HTC G7 which was placed on a 1.1-meter high tripod at place P and each took 4 minutes at 5 Hz frequency. At first, measurement was performed with nobody in Room 2221,
the first group of RSSI was denoted as $s_1$. Next, two groups of RSSI data ($s_2$ and $s_3$) were obtained separately with the author standing still in a randomly choosing place and with the author moving randomly in Room 2221. Then, the forth group of RSSI data $s_4$ consist of two parts. The first part of RSSI data were collected for a period of 2 minutes with the author standing at P1 (as shown in Fig. 9) which was close to place P and the back to AP2 as shown in Figure 3. The other 2 minutes measurement was performed with the author moving to the opposite place P2 (as shown in Fig. 9) with the back to AP1. Finally, the last group of RSSI data $s_5$ was collected with the author alternately standing at two places (P1 and P2), nearly 1 second in place P1 and 1second in place P2.

When there was a person moving randomly in the measurement environment, the RSSI data were distributed around -55 dBm as showed in Fig.11 and the histogram of the RSSI data seemed to be closer to Gaussian distribution than the other three scenarios.

The experiment results of RSSI data of AP1 and AP2 are similar, therefore, this paper reveal the statistical property of RSSI data of AP2 as representative.

<table>
<thead>
<tr>
<th>Mean (dBm)</th>
<th>Standard deviation (dBm)</th>
<th>Max. (dBm)</th>
<th>Min. (dBm)</th>
<th>Range (dBm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without person</td>
<td>-54.19</td>
<td>0.56</td>
<td>-53</td>
<td>-56</td>
</tr>
<tr>
<td>Standing still</td>
<td>-54.98</td>
<td>0.76</td>
<td>-51</td>
<td>-57</td>
</tr>
<tr>
<td>Moving randomly</td>
<td>-55.28</td>
<td>1.71</td>
<td>-50</td>
<td>-59</td>
</tr>
<tr>
<td>Alternating once time</td>
<td>-57.29</td>
<td>5.45</td>
<td>-45</td>
<td>-69</td>
</tr>
<tr>
<td>Alternating frequently</td>
<td>-57.52</td>
<td>4.92</td>
<td>-50</td>
<td>-72</td>
</tr>
</tbody>
</table>

As Table 6 shows, when a person stand still in the room, the measurement environment can be regarded as static environment. Therefore, the mean and standard deviation of RSSI data nearly have no difference. When there are some dynamic changes on the measurement environment such as a person moving in the room, the mean of RSSI would decrease and the standard deviation would increase considerably. The range of the RSSI also increases as the human behavior influence the propagation path of the real signal of APs, which cause the RSSI increasing/decreasing instantly.

Figure 10 shows the histograms and RSSI value (over time) of two groups of RSSI data of AP2. Fig. 10-a) and 10-b) reveal that in a static environment the RSSI data ($s_2$ and $s_3$) are relatively stable. The value -54dBm and -55dBm cover more than 90% of the RSSI value. In contrary, dynamic changes in measurement environment could lead to wide fluctuations in measurement RSSI value (i.e., $s_1$, $s_4$ and $s_5$) as show in Fig.11 and Fig.12.

However, two types of changes in environment cause bi-modal distribution as showed in Fig. 12-a) and 12-b). The RSSI data $s_4$ can be divided into 2 parts. The first part of RSSI data were distributed around -62 dBm and the second part of RSSI data were distributed around -52dBm. In the first 2 minutes, the direct propagation path of AP2 was fully sheltered by the author, which led to the received signal energy mainly consist of the primary reflection. Moreover, as the author was standing very close to the receiver, a few primary reflections were also sheltered. As a result, the mean value of RSSI in the...
first 2 minutes are almost 10 dBm smaller than the latter, which means the receive signal energy is 10 times smaller than the latter. Consequently, the combination of the two parts of RSSI led to a bi-modal distribution. Relatively speaking, as the rapidly changes in measurement environment, the RSSI data \( s_t \) rapidly fluctuated in a small scope of time. The regularly changes in environment lead to the RSSI data distribute around -53 dBm or -61 dBm. As a result, the RSSI data also appeared a bi-modal distribution.

The two types of changes in environment are very representative of the cause of bi-modal distribution.

When Gaussian distribution is used to model the RSSI distribution for indoor positioning system, it is essential to have some person moving randomly while collecting the RSSI values for the fingerprint and to avoid the two types of representative human behaviors that could cause bi-modal distribution.

V. CONCLUSION

This paper investigates the impact of hardware on RSSI and characterizes the distribution of RSSI. The RSSI data collected by four Android mobile phones were analyzed. By comparing the RSSI data of four mobile phones, the differences between different phones in terms of the mean, standard deviation, and range of RSSI are evaluated. The experimental data shows that the mean value of the RSSI data collected by different phones varies significantly, sometimes as large as 25dBm, even in the same time and place. The variation range of the RSSI data differs because of the different shifting mechanism used by different smart phones to covert the real received signals to the RSSI values in dBm. Furthermore, our investigation of the RSSI distribution indicates that when skewness and kurtosis coefficients are taken into account, using the Gaussian distribution to model the RSSI is not accurate. If Gaussian distribution must be used, adjusting the standard deviation \( \sigma \), would lead to a better curving fitting. The impacts of human behavior are explored in this paper and two types of human behavior are revealed to be the cause of bi-modal distribution. The experimental data shows that the RSSI data are relatively stable when the measurement environment is static such as nobody or one person stay still in the room. However, with one person moving randomly in the measurement environment, the RSSI data are distributed around a center value like Gaussian distribution. Furthermore, the experimental results show two types of human behavior could result in bi-modal distribution. The result could assist designing position algorithm and analyzing the accuracy of position system.

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