Wi-Fi CSI-based Human Presence Detection Using DTW Features and Machine Learning

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***Abstract*—With the development of smart devices, human detection and localization became important tasks for several applications including security, healthcare monitoring, entertainment, and so on. Existing signal-based detection systems, mostly focus on detecting human activities and classifying them by Machine Learning (ML) methods, like Support Vector Machine (SVM) and Random Forest (RF). This paper focuses on device-free presence detection. We propose a specific setup for collecting Wi-Fi based Channel State Information (CSI) data for detecting human presence. The proposal includes the application of Dynamic Time Warping (DTW) algorithm features to compare the differences between empty rooms and filled rooms. The proposed architecture and approach achieves competitive accuracy when compared to the existing technologies.**

***Index Terms*—Human presence detection, channel state information, Wi-Fi, DTW, Machine Learning**

I. Introduction

Recent advances in science and technology, especially Sensor Networks, Ubiquitous Computing, and Artificial Intelligence (AI), enabled the development of smart environmental monitoring systems. Those systems provide an environment aware of and responsive to humans. One basic requirement of those systems is the need to sense human presence in the environment [1].

There are different approaches to human-sensing, for example including a device-based, which requires the person to wear or carry a device/sensor, and device-free, which uses environmental sensing elements to monitor without requiring the human to carry any device or sensor [2]. The device-free approach is more convenient for users, deployment, and monitoring procedure. In this paper, we focus on device-free human-sensing.

A wide range of technologies can be used in the device-free human-sensing, such as sound sensors, image sensors, and electromagnetic signals. The electromagnetic signal use is not as privacy-intrusive as image and sound usage. Also, Radio Frequency (RF) signals can trespass obstacles, does not require ambient light, and can be performed by off-the-shelf commodity devices, such as Wi-Fi routers [2], smartphones, and single-board computers.

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RF signal waves are affected by human movements and/or presence, that can change the characteristics of the waves that reach the receiver [3]. These changes can be recognized in a dataset called Channel State Information (CSI), that provides information at the physical layer as the signal amplitude, phase, and/or Received Signal Strength Indicator (RSSI).

Several studies propose CSI-based solutions for human-sensing and activity recognition, such as sleep monitoring, vital signs monitoring, fall detection, localization and tracking, activity monitoring, people counting, and so on [4]–[6].

In this paper, we propose a system to detect human presence in CSI-monitored environments. The proposed monitoring system uses an off-the-shelf Wi-Fi router, a notebook, and a Raspberry Pi 4. The Notebook and Wi-Fi router work as an Access Point (AP) and a client respectively. The traffic exchanged between them is monitored by the Raspberry Pi 4 using Nexmon CSI [7], a firmware customized to collect CSI data.

A CSI dataset was populated with 25 participants data collections. This dataset has the endorsement of the Research Ethics Committee, belonging to the National Health Council of the Brazilian Ministry of Health. The data collection project was approved under CAAE authorization No. 54359221.4.0000.5243. In addition to participant data collection, empty room scannings were also added to our dataset, which was then processed. The Dynamic Time Warping (DTW) [8], [9] features from a comparison with a reference empty room are used to feed machine learning models and perform human presence detection. Classification algorithms were used to determine the presence or not of a participant in the room.

We summarize the main contributions of this work as follows:

- Determining an experimental setup and using empty room collections as reference to determine the presence or not of a person in a room;
- Apply DTW for determining similarity between two temporal sequences (empty room and filled room), which may vary depending on who is in the room, to determine if the room is empty or not;

- Regarding performance, comparing different ML models considering balanced and unbalanced data.

The remainder of the paper is structured as follows. Section II brings an overview of CSI systems. Section III presents human-sensing systems using Wi-Fi CSI found in the literature. The data collection and processing steps are described in Section IV,. Section V presents machine learning algorithm results, and finally, Section VI discusses conclusions and future work.

II. CSI Overview

A smart and responsive environment, capable of detecting, measuring, and collecting information about the environment and using that information, can be designed using RF technologies, such as Wi-Fi, combined with signal processing and machine learning techniques [4]. One specific set of communication link characteristics used for that purpose is the Channel State Information (CSI).

In the IEEE 802.11g/n/ac specification [10], the physical layer of Wi-Fi systems uses orthogonal frequency division multiplexing (OFDM) technique for both 2.4GHz and 5GHz frequency bands. OFDM is a modulation technique that uses a pre-defined number of orthogonal subcarriers [11]. In addition, information can be independently transmitted over different OFDM symbols. The OFDM features make it a good solution for multipath channels and also for Multiple-Input Multiple-Output (MIMO) systems [12].

To measure CSI, the Wi-Fi transmitter sends Long Training Fields (LTFs), which contain predefined information in each subcarrier, in the frame preamble. The Wi-Fi receiver estimates the CSI using the received signal and the predefined LTFs. The amount of collected data depends on the channel bandwidth, that determines the number of subcarriers, and the number of antennas used.

Considering a MIMO Wi-Fi system operating under IEEE 802.11n specification, and with m transmitting antennas and n receiving antennas, the signal that contains the estimated CSI of each data stream can be mathematically expressed as in Equation 1. The $\boldsymbol{h}_{i,j}$ represents the CSI between the i-th transmission antenna and the j-th receiving antenna.

$$\mathbf{H} = \begin{pmatrix} \boldsymbol{h}_{1,1} & \boldsymbol{h}_{1,2} & \dots & \boldsymbol{h}_{1,n} \\ \boldsymbol{h}_{2,1} & \boldsymbol{h}_{2,2} & \dots & \boldsymbol{h}_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{h}_{m,1} & \boldsymbol{h}_{m,2} & \dots & \boldsymbol{h}_{m,n} \end{pmatrix}. \tag{1}$$

Let c be the number of subcarriers used to estimate CSI, thus, the state information of the channel established between a pair of antennas (i, j) can be mathematically represented by a vector with c elements. Using $\boldsymbol{h}$ to represent a generic $\boldsymbol{h}_{i,j}$, in Equation 2.

$$\boldsymbol{h} = [h_1, h_2, \dots, h_c]^{\mathrm{T}}. \tag{2}$$

The CSI data can be used to provide information about the environment and estimate changes and phenomena that occur over time, such as human presence detection.

III. Related Work

Presence detection systems have been widely studied in the literature [13]–[16]. A significant part of the proposed technologies to detect and/or localize human presence are device-free. One of the possible solution found in the literature is based on Received Signal Strength Indicator (RSSI), which usually provides a measurement of how well your device can hear a signal from an access point or router. Another found solution is based on Wi-Fi CSI. Solutions based on CSI provide more detailed information about the systems than those based on RSSI. Its high resolution allows CSI-based technologies to achieve better performance.

In [13] for example, the authors present an Indoor device-free motion detection system, named FIMD, to overcome the limitations of RSSI-based systems. In this regard, FIMD explores properties of CSI from physical layer in OFDM systems. The method is designed based on the insight that CSI maintains temporal stability in a static environment, while it exhibits burst patterns when motion takes place. The article presents a vast introduction, which contains a variety of options for motion detection, and then compares them with RF-based systems, showing advantages and disadvantages. Afterwards, it compares RSS and CSI metrics, presenting the main points that turn CSI into a promising metric. Results presented show a detection rate greater than 90%.

Based on understanding human motion-induced signal attenuation reflected in CSI information, the authors of [14] proposed a system called DeMan, a unified scheme for non-invasive detection of moving and stationary human using commodity Wi-Fi devices. DeMan uses amplitude and phase information of CSI to detect moving targets. It considers human breathing as an intrinsic indicator of stationary human presence and adopts sophisticated mechanisms to detect particular signal patterns caused by minute chest motions, which could be destroyed by significant whole-body motion or hidden by environmental noises. Unlike many other approaches, the authors emphasize the calibration-free and the concern about stationary scenarios, which they solve using a breathing rate. This concern made them build a low error rate and accurate approach. DeMan achieves detection rate of around 95% for both moving and stationary people, while it identifies human-free scenarios by 96%, all of which outperforms existing methods by about 30%.

In another approach, the work discussed in [15] presents a device-free presence detection, and localization algorithm, bolth based on Wi-Fi CSI and support vector machines (SVM). The process goes through the CSI data collection, feature extraction, model training (to establish the presence detection classifier), and the relationship between CSI fingerprints and locations, and classification to detect presence or regression to estimate locations. The evaluation results show that the system is reasonably efficient for presence detection, achieving the detection precision of more than 97%. However, localization evaluations present moderate results which demonstrate the method does not achieve high accuracy, obtaining localization errors up to 3m.

Also, in [16], the authors proposed a system to detect static humans through estimating the breathing frequency by exploring the phase information of CSI. They got more robust data by fusing subcarriers and filtering out environmental noise by adopting Butterworth filter and using Hampel filter before and during wavelet denoising. It presents a distinct way of pre-processing data. What differentiates is the Hampel filter used in two different stages of pre-processing. The results demonstrate that the method is reasonably accurate when the distance between the router and the human is up to 0.8 meters and declines gradually when the distance increases. The results show that detecting accuracy can achieve higher than 95% and averaged evaluating accuracy can reach 89.8% with the proposed system.

Works such as those mentioned in this section show good results in the presence detection requirement. The most resent works have the best detection rate. With the intention of continuing to improve these results, this article proposes an alternative for presence detection that achieves an accuracy of up to 99% using SVM. In the following sections, proposal and results are presented in more detail.

IV. Proposal and Experimental Methodology

In the light of the existent researches, we propose a monitoring system that uses an off-the-shelf Wi-Fi router, a notebook, and a Raspberry Pi 4 to determine whether there is a person at the room or not. The traffic exchanged between the AP and the client is monitored by the Raspberry Pi 4 using Nexmon CSI [7], a firmware customized to collect CSI data through which we can identify the human presence.

In this section we present the proposed experimental setup used to collect CSI data, the performed signal processing, and we also describe the machine learning techniques used. The proposed methodology is divided into two stages, the first one is related to data collection and to the physical arrangement of elements in the collection room. The second stage refers to the analysis of the collected data and how they were manipulated to obtain the results. Figure 1 summarizes the proposed system.

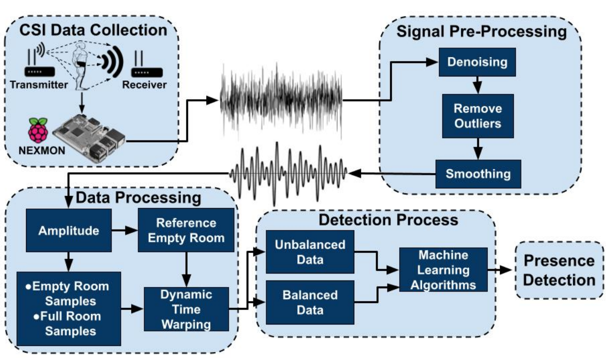

Fig. 1. Presence detection system overview.

A. Data Acquisition

For data capture we displayed an Wi-Fi network in a room in the MidiaCom Laboratory at Fluminense Federal University. Figure 2 illustrates our experimental setting in which the transceivers are placed close to the volunteer and also to the Raspberry. The distances between the participant and the equipment were set as 1m. This collecting room was used to capture data from all participants.

For collecting, we use a traditional Wi-Fi network, where a Wi-Fi client pings a Wi-Fi router. The network is configured in the 5GHz frequency band and uses a channel with a bandwidth of 80MHz, that is, a total of 256 subcarriers, of which only 234 subcarriers are considered, since we have pilot and null subcarriers. Next, a Raspberry Pi 4B was modified on its wireless board to capture and collect the CSI data. This modification is carried out by the NEXMON-CSI firmware [17]. The Raspberry performs capture and collection at an interval of 60s.

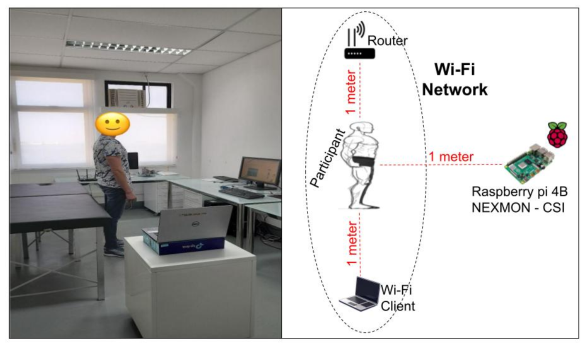

Fig. 2. Experimental setup.

In this work, we captured collections from 25 participants including 17 men and 8 women. Each participant performed 17 different positions and/or movements during the capture at the collecting room. Specifically for the case of presence detection, the position is indistinct, once what really matters is the presence of the participant in the room. There were 25 participants and 17 different positions for each participant, which gave us a total of 425 instances with filled room. Within each set of collections, a collection of an empty room (without each participant) was also performed, which gave a total of 25 collections for 25 participants. This data collection represents what we called our unbalanced dataset.

The data collected from an empty room (without human presence) were used to have a balanced dataset. In total, 425 empty room collections were captured, representing a total number of instances of rooms with human presence. Each collection is stored in a file that keeps samples of the signal that define the 60s duration of the collection for each used subcarrier, in this case 234.

B. Data treatment

In order to improve the accuracy of the obtained results as much as possible, several treatment techniques were applied to the data. In this section we address several techniques such as signal pre-processing, distance between two time series, definition of unbalanced and balanced datasets, feature selection, and classification analysis. In the following we present a review of these techniques.

1) *Pre-processing*: After collecting data, we proceeded with the treatment of the collected data that comes from the wireless transmission medium. We observed that each collection contains noise and outliers. To clean the signals we applied various signal cleaning techniques. The Hampel filter was used to remove noise, the Moving Average filter was used to remove outliers and smooth the ripple, it also does a job of cleaning noise just like the Hampel filter. Subsequently, we obtain the amplitude of each signal, that is, for each collection we have 234 subcarriers, then we have the amplitude of those subcarriers throughout the 60s that the collection lasted.
2) *Distance between signals:* With this technique we can obtain new features from the amplitudes of the collected signals. The chosen technique was the Dynamic Time Warping (DTW), which is an algorithm that compares the similarity or calculates the distance of two time series. Specifically, in this work the collection of an empty room was considered as a reference. Then the similarity (DTW) between the reference signal and the signal corresponding to each of the instances used is compared; and then this similarity is used as features. In this work, the time series are for each subcarrier. For the DTW algorithm, it is not important that the time series have the same size, but in this application all time series are of the same size since they represent the collections during 60s [8].
   For this step, the empty room considered as a reference was chosen at random, since they all presented the same behavior pattern. Then, the reference empty room was compared against each of the 425 empty room collections using DTW. Likewise, the reference empty room was also compared with the 425 collections from the room with human presence, again using the DTW algorithm.
   Then, each comparison is made between the equivalent subcarrier of each collection, that is, first reference empty room subcarrier versus first collection subcarrier of a filled room or empty room, and so on. After the comparison, each collection returns 17 instances with 234 features for a given instance. To which we will have 425 instances, as that we have 25 participants. The data for empty rooms are processed in the same way. At the end, we will obtain a matrix of 850 instances (empty rooms and filled rooms) and each instance has 234 features that are the distances calculated by the DTW algorithm for each pair of subcarriers. One advantage of using DTW is its low computational complexity.
3) *Unbalanced and balanced datasets:* The formation of the datasets is based on the amount of collected data during the testbed. As already described in item 1, the datasets are made up of the number of samples per participant, being a total of 425 instances that represent data from filled rooms. In the case of an unbalanced dataset, it was considered that it had a total of 450 instances, with 25 instances only representing 25 empty rooms, one for each participant. It was considered for analyzing how the classification algorithm acts in this situation. The majority class has been defined as the presence of a person in the room, while the minority class is the non-presence of a person in the room (empty room).
   Aiming to avoid the presence of a majority class, we decided to collect more data of empty rooms, reaching a total of 850 instances for a balanced dataset. With this procedure, it was possible to remove the majority and minority classes. It is worth mentioning that the increase in the minority class was not gradual and it took from 25 until 425 instances to make the equivalence of the instances of the majority class.
4) *Feature selection:* In this work we have 234 features that are used as input for machine learning algorithms. A selection of the features was made to show that the number of features does not affect the results and that it can generate overfit in the model. For this, a selection of features was made through univariate statistical tests. The SelectKBest [18], [19] technique performs this selection of the best features using regression functions, which helps to reduce the training process of a large dataset and eliminates the least important part of the data.
5) *Classification analysis:* We used different algorithms such as Naive Bayes, J48, SVM, and Random Forest [20], [21] to classify empty and filled rooms. For Naive Bayes, the default parameters were used without a priori class specification. For the J48 algorithm, an entropy criterion and a tree with depth of 3 was used. In SVM we use a linear kernel, thus following a linear model. For Random Forest, a number of 100 estimators was left, which is the default parameter in the number of trees within the forest. In this analysis, all the algorithms received 70% of the data for training and 30% for testing. In the case of the unbalanced dataset, we forced the minority class to follow the mentioned data division.

V. Obtained Results

In this section, we present the results obtained by performing the steps presented in Section IV. The results were obtained with the collaboration of 25 volunteers. Each of them contributed to a collection of 17 different positions/activities, which means that we consider the room filled, regardless the position and/or performed activities. It is worth mentioning that the position of the person in the room is indifferent since the present work focused on the detection of human presence within an environment. The sampling rate was 9 samples per second. For the implementation, python libraries were used.

The obtained results are presented in two stages. The first stage shows the results obtained from an unbalanced dataset and the second stage shows the results obtained from a balanced dataset as described in Section IV.

As already mentioned, we have a total of 234 attributes obtained from the DTW application. For the obtained results, all the attributes of the datasets were considered balanced and unbalanced. Table I summarizes the accuracy achieved for each classification model: SVM, J48, Bayes Naives, and Random Forest. As can be seen, with the classifiers and an unbalanced dataset we obtained an accuracy of 79.41% when applying the Naive Bayes algorithm and 94.85% in the case of J48. These results indicate good classification handling but may also indicate biased classification to the majority class.

TABLE I
ACCURACY OF MODELS (%).

Dataset	SVM	J48	Bayes Naives	Random Forest
Unbalanced data	91.17	94.85	79.41	94.11
Balanced data	99.21	97.26	96.48	98.43

For a more detailed analysis using the unbalanced dataset, we also present in Table II the Precision, Recall, and F-Measure metrics, in addition to the previously mentioned accuracy. In the case of the Precision metric, we observe values below 46.97%, with the exception of the J48 algorithm, which reached 97.41%, but its Recall metric is 56.25%, which indicates that the model did not perform a correct classification. In addition, the F-Measure metric, which shows the relationship of the two previous metrics, does not exceed 59.78%, which indicates that the accuracy obtained is not completely correct and the classification is not well done. The used model classified based on the majority class (empty room) and gender, an accuracy that is not really representative. Thus, the model classified as empty room more times than a filled room.

TABLE II
RESULTS FOR UNBALANCED DATA (%).

Algorithm	Accuracy	Precision	Recall	F-Measure
SVM	91.17	46.97	48.44	47.69
J48	94.85	97.41	56.25	59.78
Bayes Naives	79.41	46.55	42.19	44.26
Random Forest	94.11	47.06	50.00	48.48

Aiming to deal with the previously reported results with an unbalanced dataset, a balanced dataset was used with the classification algorithms. This dataset follows the same structure reported in Section IV-B. In Table III we present the obtained results for a balanced dataset. We observe that the accuracy increases relatively if compared with the results of the unbalanced dataset. We have a base accuracy of 96.48% for the balanced compared to 79.41% for unbalanced dataset. In addition, the best result is obtained by the SVM algorithm, an accuracy of 99.21%, compared to 91.17% in the case of an unbalanced dataset.

As we can notice, accuracy is improved over the previous models as well as the Precision, Recall, and F-Measure metrics. In the case of the Precision metric, a gain of 52.25% is observed with respect to the previous model. It reaches values of 99.22% in the best case and 96.48% in the worse case. The Recall metric also reaches a value of 99.01%. Thus, we obtain an optimal F-Measure ratio for classification with values between 96.48% and 99.11% for the SVM algorithm. The false negative cases are probably due to the presence of other people close to the room during data collection. Thus, we observed that the classification using a balanced dataset is the ideal. Our proposed model was able to well determine whether or not there is a human presence in a room.

TABLE III
RESULTS FOR BALANCED DATA (%).

Algorithm	Accuracy	Precision	Recall	F-Measure
SVM	99.21	99.22	99.01	99.11
J48	97.26	96.90	97.66	97.28
Bayes Naives	96.48	96.72	96.48	96.48
Random Forest	98.43	98.48	98.44	98.44

So far, the obtained results show a good accuracy for the human presence classification when using a balanced dataset. However, these results are obtained using all 234 features calculated for each subcarrier. At this point, we want to investigate the effects of the number of used features.

For this, we ran more experiments using the SelectKBest technique as a feature selector. We used different quantities of features (5, 10, 20, 50, 100, and 234). Figure 3 presents the obtained results considering different amounts of features. As we can see, with 234 features it already represents a good accuracy in the 4 used algorithms, but a way to optimize this accuracy is the reduction of used features. Thus, we show that by selecting 5 features, the best classification result is obtained, reaching an accuracy of 99.98% with Random Forest algorithms. Also, we show that with 10 features we still reach optimal accuracy, and with more than 20 features the accuracy declines. It shows that the initial results are good, but that the model can still be further optimized. This is due to the fact that the 234 features can generate an overfit in the model.

The presented results were based on a single reference empty room. To evaluate the impact of changing the reference room we switched to any other empty room of reference and rerun the experiments. For this, we conducted empty room collection with a duration of 6 hours, then we took a reference empty room at every 1-hour intervals, which generated a total of 5 reference rooms. In Table IV we show the obtained results considering these 5 reference empty rooms and the Random Forest algorithm (Random Forest:1 until Random Forest:5). We used the Random Forest algorithm since it obtained the best performance using 5 features as shown in Figure 3.

As we can see the variation of the results is minimal and almost null when varying the reference room. Table IV shows that the accuracy remains above 98.04% in the worst case, and the other metrics such as F-measure also show the same

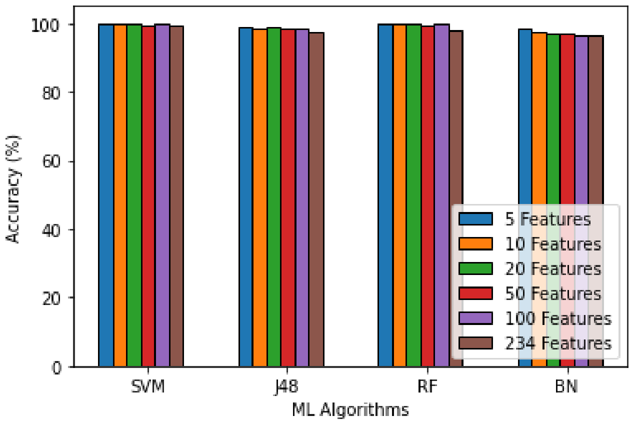

Fig. 3. Accuracy of different algorithms with different amounts of features.

TABLE IV
RESULTS WITH DIFFERENT REFERENCE EMPTY ROOMS

Empty room	Accuracy	Precision	Recall	F-Measure
Random Forest:1	99.22	100.00	98.46	99.22
Random Forest:2	99.61	100.00	99.23	99.61
Random Forest:3	99.98	99.97	99.99	99.98
Random Forest:4	98.82	99.22	98.46	98.84
Random Forest:5	98.04	99.21	96.92	98.05

behavior. For all the algorithms used in this work, the variation lies between 0.37% and 1.93% when using different reference empty rooms with a selection of 5 features. Therefore, we show that the previous results represent the classification of the room. Also, by selecting any empty room as a reference will not change considerably the results and remain stable.

VI. CONCLUSIONS

In this work we proposed to use Wi-Fi CSI data in a device-free system to determine the presence or not of an individual in a monitored room. We also proposed an experimental setup that involves empty room monitoring and comparison with filled room. Also, we used different DTW features and different algorithms to compare the collected data and determine either the room is empty or not. Experimental evaluations showed that, by balancing the collected dataset, the proposed approach can achieve an accuracy of 99.21% when using the SVM algorithm.

In addition, we showed that the number of features initially used does not affect the good performance of the model and classifiers, but it can be optimized. Thus, we selected the 5 best features and using the RF ML algorithm, the accuracy of 99.98% was maintained. Also, we compared the use of several empty reference rooms to see if it affects the variation of the results obtained. As we can notice any reference empty room can be used.

As future work, we intend to use a broader dataset and continue using balanced data to make more rigorous tests of our model, in addition to incorporating new deep learning algorithms.

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