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Crowd Size Estimation with Passive Electromagnetic Sensing

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***Abstract*—Crowd size estimation has become of even greater significance than before COVID-19 restrictions. At the same time, wireless technologies are ubiquitous and change rapidly; we hypothesise that we can estimate crowd sizes from electromagnetic (EM) activity, agnostic from the used communication technology. In this experimental study, we investigate crowd size estimation based on the activity that ambient WLAN devices generate inside specific WLAN channels. By recording and analysing this EM activity, we tested if this corresponds to the crowd size at a large music festival with thousands of attendees. We identify and compare trends within a data set of 186 samples over three consecutive days. We demonstrate a significant correlation between our approach and the data of three other crowd estimation systems: entrance and exit counts, MAC address counts, and device-free sensing using sub-GHz attenuation. Our study is the first step to passively and technology agnostic estimate large crowd sizes by capturing the electromagnetic activity inside the 2.4 GHz band with Software Defined Radios.**

***Index Terms*—passive sensing, crowd size estimation, JC&S**

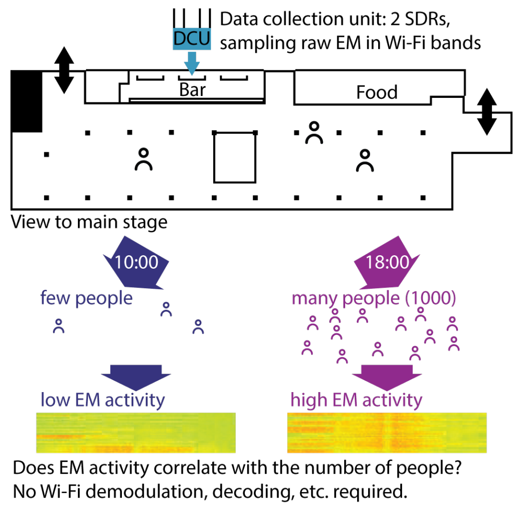

Fig. 1. We captured electromagnetic (EM) samples in WLAN bands 1, 6, and 11 at an environment that held 1500 people at full capacity. Our hypothesis is that we can estimate the crowd size directly from EM activity in contrast to typical CSI approaches based on Wi-Fi pilots.

I. Introduction

The estimation of crowd sizes has sparked a lot of attention during COVID-19 and in post-pandemic times. Crowd sizes are of great importance to safeguard public safety. Many solutions already have been deployed and studied in the past. A popular solution for estimation are optical cameras that apply image analysis. Nevertheless, they have several constraints. They are sensitive to lighting and weather conditions, field of view and there are privacy concerns about the saving and usage of the camera footage. Another technique is the use of Wi-Fi counters that collect MAC-addresses. Privacy concerns regarding the captured data do exist here as well.

Nevertheless, there are new upcoming techniques that can tackle these issues. The growing physical layer capabilities of Wi-Fi such as Orthogonal Frequency Division Multiplexing (OFDM) in combination with Multiple-Input Multiple-Output (MIMO) systems, induce a new trend in the way that Wi-Fi signals are used for high bandwidth communication and sensing purposes. Within the conceptual idea of Wi-Fi sensing, we expect that a moving person or object will affect the Wi-Fi radio waves. This can be in terms of signal attenuation, frequency shifts and through various propagation paths [1].

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We define passive sensing as the detection of objects or persons via wireless signals, without relying on the users or objects to be equipped with any sort of transceiver. Also referred to as device-free or non-invasive sensing. According to [2], the current and most popular passive Wi-Fi sensing methods can be categorised into Received Signal Strength Indicator (RSSI), Wi-Fi radar and Channel State Information (CSI). The RSSI is a channel quality indicator. It is the strength of a received signal measured at the receiver's antenna. This value is determined by the transmission power, the distance between transmitter and receiver, and the radio environment [3]. Wu et al. demonstrate that the variance of RSSI values from a static receiver can be up to 5 dB per minute and is very sensitive to multipath effects [4]. These high fluctuations are the reason why this method is applied less frequently. Zaidan et al. present a people counting system based on passive Wi-Fi RSSI which was tested in a conference room with one access point achieving an accuracy of 93.17% while maintaining line of sight [5].

A Passive Wi-Fi Radar system (PWR) commonly uses synchronised Software Defined Radios (SDRs) to sense. Usually, the reference signal is expected to be received from a direct path with the signal source without strong multipath impact and reflection components. The surveillance signals are expected to be received from the other paths, which potentially contain the reflections from targets of interest. The differences between the reference signal and the surveillance signals are then extracted by applying the Cross Ambiguity Function (CAF). The CAF calculates range (bistatic distance) and Doppler (bistatic velocity) information. However, the Doppler information is used more often since it provides fine-grained information while the range resolution is rather coarse-grained. The acquired time and frequency domain differences can be eventually converted into Doppler spectrograms [6]–[9].

In passive Wi-Fi sensing, plenty of research is also aimed towards the investigation of CSI characteristics [4]. The CSI information describes how a signal propagates from a transmitter to a receiver and represents the combined effect of scattering, fading, and power decay with distance. Therefore, it is possible to adapt transmissions to current channel conditions [10]. CSI obtains the amplitude and phase information of a signal at the sub-carrier level. The retrieved values essentially characterise the Channel Frequency Response for each subcarrier between each transmit-receive antenna pair. Therefore, it can deliver very fine-grained information about a communication channel. Furthermore, it is possible to simultaneously extract the CSI of multiple channels [4].

The use of these techniques in passive Wi-Fi sensing has been investigated thoroughly over the years. It has many application fields e.g. health monitoring, gesture recognition, through-the-wall sensing, biometric measurements and sign language recognition [11], [12]. Singh et al. for example present a proof of concept setup where they use the RSSI values of LoRaWAN and a multilayer perceptron artificial neural network to predict the weekly plant growth in greenhouses [13]. Recently, it has even become possible to sense micro-activities such as respiration and sleep monitoring, lipmotion and keystroke recognition using CSI [2]. However, the research of people counting and crowd size estimation using the current techniques of passive Wi-Fi sensing is very scarce. The available literature only shows experiments for small scale scenarios. Remarkably, there are no studies available where this is tested on a large scale and we do not know what the crowd size estimation and accuracy can be. Here, our novelty is to explore passive Wi-Fi sensing in large crowds.

Concretely, we propose a new approach to passive Wi-Fi sensing by using SDRs to capture the EM waves of ambient WLAN devices. This will be translated to activity in the frequency spectrum and subsequently can be correlated to crowd size. The goal is to estimate large crowd sizes with a minimal amount of data in a privacy-preserving manner. More specifically, we conducted measurements at a large music festival with thousands of attendees. Figure 1 depicts an overview of the area where we executed these measurements. Our findings show that we can see a change in activity when comparing opening and closing hours of the festival. In addition, a moderate correlation can be found when we compare our data with two validated data sets.

The remainder of this paper is organised as follows. In Section II, we present our experimental setups and data collection sequence at the festival followed by an explanation and equipment setup of the validation system in Section III. Subsequently, in Section IV, we examine the achieved results with an in depth discussion. Finally, we conclude this paper and have an outlook on the future work in Section V.

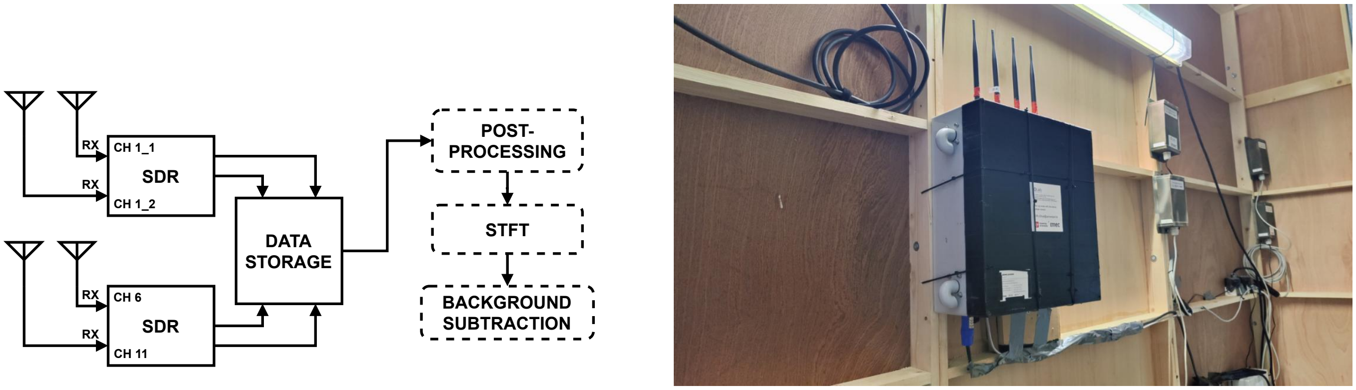
II. Methods

The measurements took place at the music festival Tomorrowland, organised during three weekends in July 2022 that hosts almost 200,000 attendees per weekend. We conducted measurements at the "Business to Business" (B2B) environment, which is part of a three-storey temporary VIP environment. The VIP environment consists of the "Main Comfort" at the ground floor; the B2B at the first floor; and the "Skybox" at the second floor.

To enter these environments, each festival attendee needs to scan their festival bracelet. Each subsequent floor requires a higher tier of VIP access to enter, so that each floor has a separate entrance and exit. Each floor covers an area of about $1500\,\mathrm{m}^2$ and is half-open with a view of the main stage of the festival. Our measurement setups were partially placed behind the bar of the specific floor, separated by a wooden wall construction. We deployed three measurements setups. One consisted out of an SDR Data Capture Unit (DCU). The second measurement setup consisted out of four Wi-Fi counters. These devices scan each 2.4 GHz WLAN frequency band in a random manner while the software collects the MAC addresses of the ambient wireless devices and anonymises them in order to safeguard the privacy of the festival attendees. The third setup consists out of a Wireless Sensor Network (WSN) which we used for validation. A fourth measurement setup that scans the festival bracelets of the attendees, was provided by the organisation and was used as ground truth reference and as validation data set.

To measure EM activity, we build a DCU that is based on SDRs. This unit was placed at a height of 1.8 metres, containing two Ettus Research Universal Software Radio Peripheral (USRP) B210 SDRs and an Intel NUC. It is equipped with four omnidirectional dipole antennas which indicates that we use the two RX channels of each SDR simultaneously. The RF front end chip inside the B210s has an instantaneous real-time bandwidth of 56 MHz allowing us to capture two 20 MHz bands concurrently. This unit collects the electromagnetic activity in the Wi-Fi bands but will not gain us the number of people that are present in the B2B environment. Denis et al. show that the amount of persons can be derived by correlations and thereafter by linear extrapolation [14]. Figure 2a depicts the system overview of the DCU while Figure 2b depicts the measurement setups at the B2B environment.

For the data capturing, we made use of the open-source tools GNU Radio, the USRP Hardware Driver (UHD) and several Python scripts for the automation of the data capturing process. The communication link between GNU Radio running



(a) (b)

Fig. 2. Data Capture Unit (DCU) used to measure electromagnetic activity in the WLAN frequency bands. (a) System overview of the DCU. (b) Deployment of the DCU and four Wi-Fi counters behind the bar of the B2B environment.

at the host machine and the SDRs happens through the use of the UHD. Scanning the entire Wi-Fi band continuously would be a costly and bandwidth intensive operation. Therefore, we focus on the three most used Wi-Fi channels in the 2.4 GHz band that do not overlap and do not interfere with one another, namely channel 1 at 2412 MHz, channel 6 at 2437 MHz and channel 11 at 2462 MHz. Note that we redundantly record channel 1, since we have four RX channels at our disposal. We configure the SDRs to capture samples at a rate of 20 MS/s for a duration of 10 seconds per channel. The current measurement setup does not allow us to record raw I/Q samples i.e. electromagnetic waves continuously due to storage limits. Therefore, we chose to record samples in a random manner within a predefined time frame. This approach allows us to collect a limited amount of samples while representing a valid unbiased data set. The software that is running on the NUC, compares a timestamp list with the current time and starts a sampling procedure when needed. The data collection, started each festival day from 10:00 until 02:00 the next day. Table I gives a brief overview of the used measurement setups.

TABLE I
COMPARISON OF THE USED COUNTING METHODS.

Bracelet scanners	Wi-Fi counters	DFS system	EM waves DCU
2 entrance and 2 exit scanners per floor	4 Wi-Fi scanners	26 nodes	1 DCU with 2 SDRs
Entrance and exit counts	No. MAC addresses	Node-to-node mean attenuation	Mean attenuation in a WLAN channel

III. VALIDATION

We have two reference data sets to validate our captured EM waves data with, namely: the bracelet scan system and the Device-Free Sensing (DFS) system. The bracelet scan system is used to allow or deny access to one of the three VIP areas. Therefore, each floor has its own bracelet scan system. A festival attendee will get scanned when entering and exiting a certain VIP area. Essentially, it can act as a good reference regarding the amount of persons present at a certain VIP environment. We do need to note that not every bracelet could be scanned. Specific VIP guests of the festival had a different bracelet with a specific number on it in order to enter. These bracelets were visually checked when entering. Besides that, crew members and staff members were also not scanned. A final note, at the end of the festival it seemed that nobody got scanned anymore. This is to ensure smooth people flow management and avoid congestion. Another validation system is the DFS system. Denis et al. started investigating crowd estimation in large areas using sub-GHz transceivers in 2016. They have created and tested several device-free crowd estimation setups at Tomorrowland [14]–[18]. Kaya et al. explain how the setup of this system works and have made three data sets publicly available [19]. The system is based upon setting up a wireless radio frequency sensor network around the edges of a measurement environment. The network contains several battery-powered boxes called "nodes". These nodes contain an RF transceiver that operates in the sub-GHz band using the DASH7 Alliance Protocol. The nodes broadcast messages in a cyclic fashion and receive messages while other nodes are transmitting. Additionally, the network contains a "controller" that also acts as a transceiver and coordinates the cycles of the nodes in the network. Furthermore, it stores the messages received from the nodes. These payloads can be further processed eventually. Lastly, the network contains a "configurator" that sends configuration data to the nodes in the network upon request. The payload that is sent by every node to the controller is a vector consisting out of all the RSS values measured across the links between a node and its peers in the network. These signal strength values are then individually compared to their initial signal strengths in the environment with virtually no people present in order to attain the mean signal strength attenuation over time across the entire sensor network. For the setup at the B2B environment, we respectively placed 24 DFS nodes around the borders and behind the bars accompanied with a configurator and a controller. The nodes, except for the controller were placed at a height of about 1.1 m. Data was collected for the three weekends, running the system continuously for about 19 days.

IV. Results and Discussion

In this section, we investigated only the data set of weekend two to maintain clarity and overview. We have to note that we lost six sample points at the end of day three due to a crash of the DCU.

A. Short-time Fourier transform

As mentioned in Section II, the collected data is saved in a complex valued manner. To make sense of this data collection, we need to apply digital signal processing techniques. By applying the Fast-Fourier Transform (FFT) to each sample, we can achieve a rough indication of the activity in a specific WLAN channel. The FFT provides detailed spectral and magnitude information of the samples but does not reveal more context about the frequency changes that occur over time. To get a better insight into these frequency changes over time, we can apply the short-time Fourier transform (STFT). This technique segments a time-domain input signal into several frames and multiplies the signal with a specific window function and eventually applies an FFT to each frame while gaining us the temporal and spectral information of the data [20]. This combination can be depicted as several amplitude variations that can be seen as activity markers. In this way, we can get a spatial representation in the form of a spectrogram or waterfall plot which is a visual representation of the signal strength of a sample plotted over time at specific frequencies.

B. Background subtraction

Another technique that we applied is background subtraction. A technique that is also used in radar based applications to remove undesired signals [21]. While many methods can be applied to achieve this, we chose to apply a mean background removal. The mean attenuation difference per channel after applying a STFT is depicted with and without background subtraction at the bottom graph of Figure 3. The raw captured data shows a relative flat response with subtle fluctuations occurring in the four Wi-Fi channels. When we subtract the background, we see a more fluctuating response with noticeable slopes at the start and end of each festival day. To achieve these results, we apply an STFT on each background sample where we divide it into 16,384-sample segments. Each sample segment is fitted with a Hamming window and a DFT is applied on each segment. Eventually these complex values are converted to magnitudes. The STFT itself returns a matrix where,

$$S \in \mathbb{R}^{t \times f} \tag{1}$$

in which t is the time dimension represented by 12,207 time instants and f is the frequency dimension representing 16,384 frequency points. The mean attenuation of the I/Q background samples, $\overline{S_{bg}}$ is calculated by:

$$\overline{S_{bg}} = \sum_{i}^{B} \frac{S^{(i)}}{B} \tag{2}$$

where B is the number of samples used to calculate the background and i is the index of each sample in the set of background samples. This background data set consists out of samples recorded on a weekday between weekend 1 and weekend 2. On these days we know that there was little to no activity at the B2B environment.

Subsequently we need to find the mean attenuation of our I/Q data samples i.e. $a_{\neg bg}$ that will gain us the EM activity per Wi-Fi channel. The following calculation is applied,

$$a_{\neg bg} = \sum\nolimits_{t,f} \frac{(S - \overline{S_{bg}})}{N} \tag{3}$$

where, S is the short-time Fourier transform of the I/Q data samples in which these complex samples are converted to magnitude values while N is the number of elements in S. Notice that we apply almost the same process to this data set as shown in (1) but we subtract the background mean attenuation.

The STFT parameters for the background samples and data samples were chosen identically. There are four parameters that have an effect on the final STFT results we achieve. These are the FFT size, the segment size, the window type and the amount of overlap. The FFT size and segment size where equally chosen, namely 16,384. Subsequently, we chose a Hamming window to fit each segment and defined a 0% window overlap.

When looking ahead, a thorough investigation of these parameters needs to be conducted to obtain the best trade-off parameters for this specific data set. Also applying the Discrete Wavelet Transform (DWT) could gain more detailed information when compared to the STFT technique. We could also apply blob counting detection within the spectrograms. We do believe that the pixels in a spectrogram exceeding a certain threshold level will have a specific correlation to the DFS or bracelet scan data set.

C. DFS data

When inspecting the calibrated DFS data in Figure 3, we see three distinct peaks representing the three festival days. Also the opening, event and closing of each festival day can be clearly seen. These peaks seem to increase and decrease rather fast at the start and end of a festival day. During the festival, the values seem to be quite steady with small variations between 1 to 3 dB. With 24 deployed DFS nodes, there is a large number of unique links (276). Both this high number of links and the rolling mean with a window of one minute contribute to the relative steadiness of the graph.

When comparing this to the bracelet scan data as shown at the top of Figure 3, we see similarities in the peaks and troughs occurring. These similarities can also be found in the Wi-Fi counts graph. We need to note that the effects of the highs and lows are more pronounced, which is due to the cumulative count of the four Wi-Fi counters. When we look into the EM signal data shown at the bottom of Figure 3, we see that the values fluctuate heavily before the start and at the end of the festival. During the festival, fluctuations between 1 and 10 dB can be observed. These high fluctuations are

TABLE II
COMPARISON OF THE PEARSON AND KENDALL CORRELATIONS BETWEEN THE DFS SYSTEM, BRACELET SCANS AND WI-FI COUNTS.

	DFS system & Bracelet scans	*DFS system & Wi-Fi counts*	*Bracelet scans & Wi-Fi counts*
Pearson's r	0.904	0.854	0.774
Kendall's τ	0.605	0.604	0.445

TABLE III
PEARSON AND KENDALL CORRELATIONS OF THE EM WAVES DATA SET COMPARED TO THE DFS SYSTEM, BRACELET SCANS AND WI-FI COUNTS.

		EM			
		CH 1 (1)	*CH 1 (2)*	*CH 6*	*CH 11*
Bracelet scans	**Pearson's r**	0.730	0.439	0.533	0.604
	Kendall's τ	0.394	0.156	0.283	0.272
Wi-Fi counts	**Pearson's r**	0.733	0.664	0.617	0.634
	Kendall's τ	0.471	0.416	0.310	0.336
DFS	**Pearson's r**	0.843	0.732	0.773	0.777
	Kendall's τ	0.512	0.374	0.396	0.384

expected when measuring ambient EM waves. Also notice that the mean attenuation for CH 6 and CH 11 is higher in comparison to CH 1 over the weekend.

D. Correlation

While our main reference is the bracelet scans data set, the DFS data does provide changes in the data that are not captured by the bracelet scans. For instance, we can see that the bracelet scans lack the ability to provide reliable people counts when the flow of people is too high (e.g. the outflow at the end of the festival). As for the timestamps with data available for both the DFS and bracelet scans, we see a very strong positive Pearson r correlation as depicted in Table II. This correlation is comparable to the values reported in earlier research, when a similar DFS setup was used for the Main Comfort environment at the 2018 edition of Tomorrowland [14]. This very strong positive Pearson r correlation can be also seen when compared to the Wi-Fi counts. The correlation between bracelet scans and Wi-Fi counts is smaller but still strong and significant. However, the three methods show positive Kendall correlations that are significantly small which indicates that the relationships between the data sets are moderate monotonic. In Table III, the Pearson and Kendall ranking coefficients of the bracelet scans, Wi-Fi counts and DFS system are compared with the EM wave activity per channel which is measured over the entire weekend. Note that the Pearson r correlations are moderate to strong when compared to the three measurement setups but still show a significant correlation. These lower correlation values are due to the way the measurement systems work. The DFS system scans only the B2B environment while the EM waves system and Wi-Fi counters will pick up ambient activity that happens within a specific network on a specific channel and can even be affected by a specific event happening in the vicinity of the measurement environment e.g. dinner, a dance act or a specific artist playing at a nearby stage. A noteworthy occurrence is the remarkable correlation difference between CH 1 (1) and CH 1 (2). This could be due to a bad antenna connection or a configuration setting of the SDR. The probability value p is overall small ($p < 0.05$) in both tables which indicates that the correlation is statistically significant. We do need to note that the Kendall p values for correlation of the bracelet scans and EM activity are larger than 0.05. The Kendall's τ coefficients in both tables are positive but indicate a weak to moderate rank relationship. This is due to the wide dispersion of the data points as can be seen in the scatter plots of Figure 4.

We need to note that directly mapping these correlations to a specific number of people is not possible. Additionally, we notice a bizarre occurrence on the beginning of day two and three where the mean attenuation of several Wi-Fi channels is not rising directly. This could be due to some activity of the personnel on site or a channel that is not used or disabled for a limited period of time. Furthermore, sequentially capturing data samples will gain us a continuously data set which might gain more insights. Additionally, a thorough investigation of the background samples could also provide more insight into the behaviour of the channels while there is no human activity affecting the ambient Wi-Fi activity.

V. CONCLUSION

In this paper we introduced a new technique that fits within the field of passive Wi-Fi sensing. This device-free sensing method is based on capturing the electromagnetic activity that is available in a specific 2.4 GHz band. By applying several data analysis techniques, more detailed information can be revealed and shows moderate to strong positive correlations when compared to different data sets. However, the ranking correlations are overall relatively weak. This implies that there are variations in the data sets that are not explained by the number of people through the proxy of the EM waves data set. Additionally, the DFS data set, Wi-Fi counts and bracelet scan data set contain many more samples in comparison to the EM waves data set. This may be the reason why certain variations in the attenuation are seemingly not caught by the ambient EM waves. Another bias in the Wi-Fi counts and EM waves data set is that we pick up WLAN activity outside of the B2B environment. The activity we see, relies on the activity that is happening in a specific network on a specific channel.

For future work, we believe more random and smaller samples need to be taken during these events since the measurement area is subject to fast changes which is hard to capture with only four samples per hour. Further investigation regarding the data analysis e.g. optimising the STFT parameters and applying DWT is needed for this new measuring method. Capturing LTE cellular signals simultaneously can serve as a valuable reference data set. Additionally, adding strategically placed DCU's to the environment will generate more data and can give more insights regarding the environmental activity. Eventually, fitting multiple DCU's with directional antennas to pinpoint a specific measurement environment is another track to investigate.

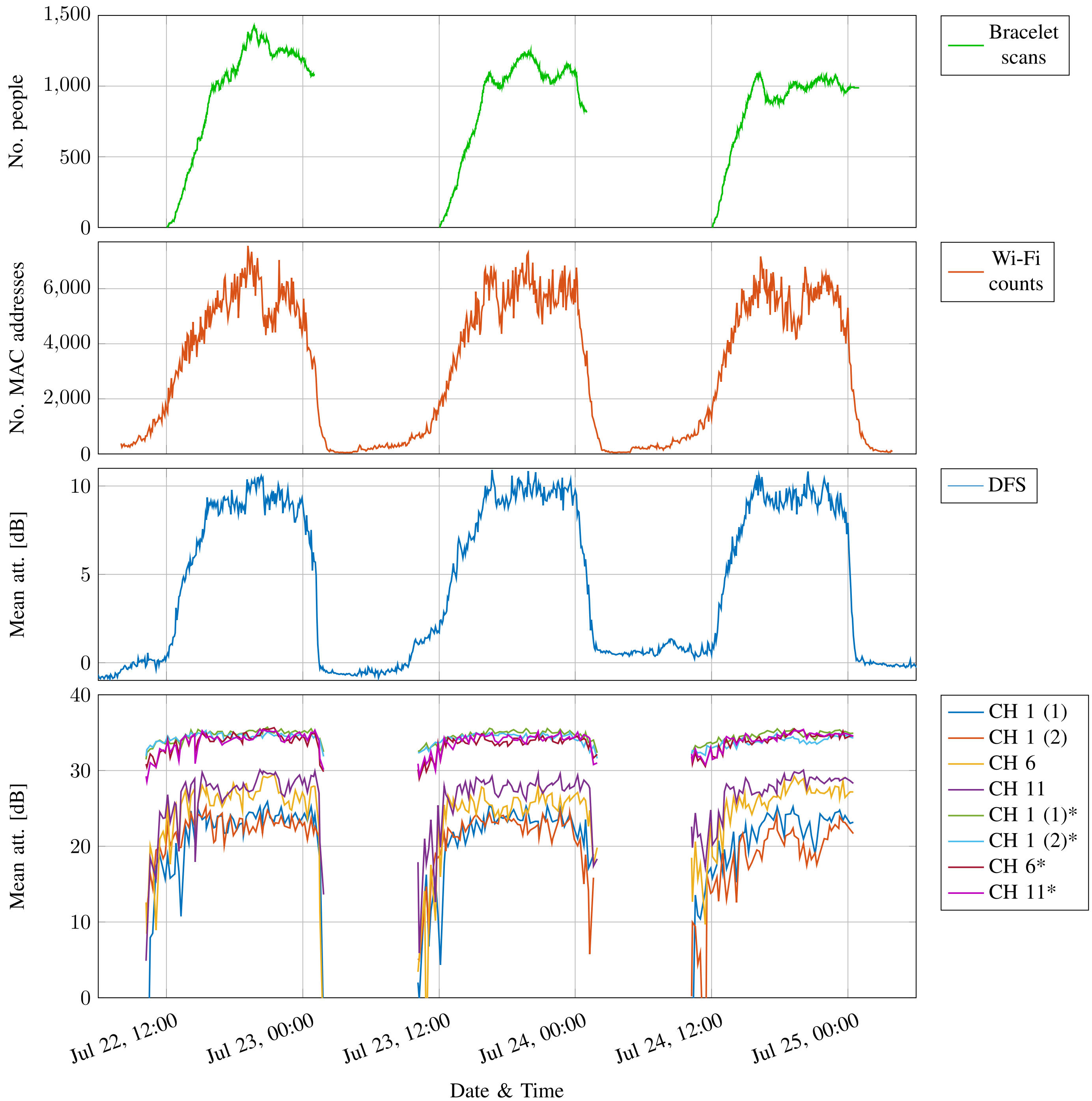


Fig. 3. The green curve shows the number of people at the B2B environment while the red curves depicts the cumulative amount of MAC addresses of the four Wi-Fi counters. Furthermore, the blue curve depicts the mean RSS attenuation of the DFS data while the eight remaining curves represent the mean attenuation of the EM waves data set. Each subset of four curves shows the attenuation with and without background subtraction during weekend two of the festival. The data without background subtraction is indicated in the legend by the asterisk symbol. As can be seen, applying background subtraction shows more detailed variation in the data.

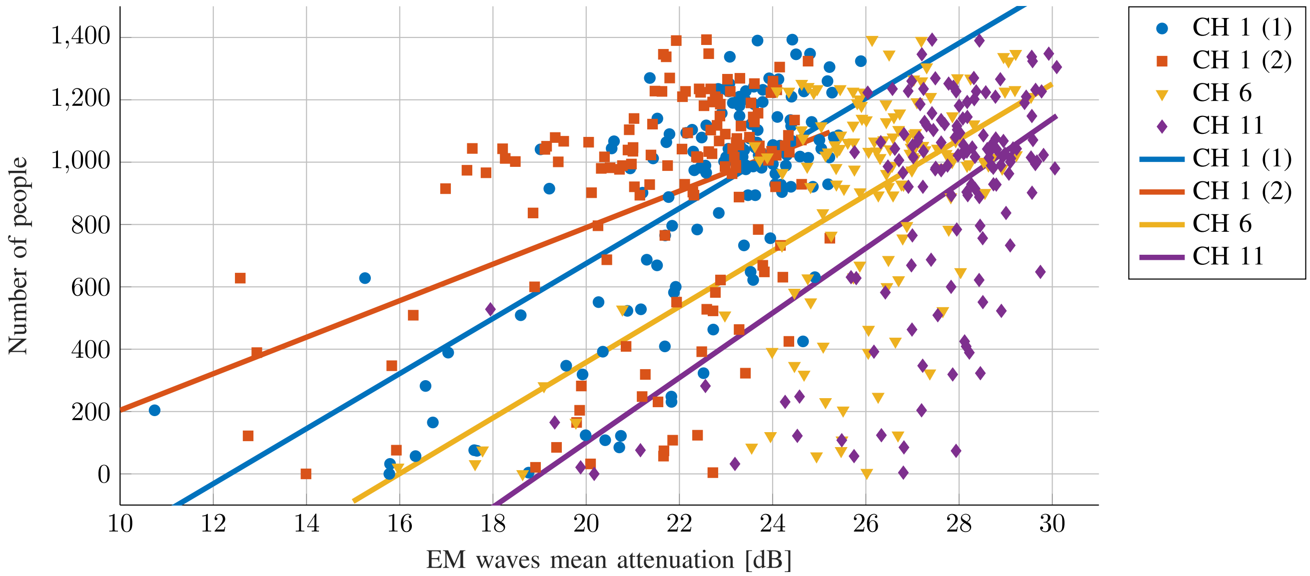


Fig. 4. Scatter plots indicating the correlation between the mean attenuation of the EM waves and the bracelet scan data extended with their respective regression curves.

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