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AI Occupancy-Tracking Platform enables Social Distancing

An AI Neural Network platform uses radio CSI (Channel State Information) to provide reliable people detection for COVID restriction compliance in Buildings, Smart Cities and Transportation.

Overview

People/crowd size counting is becoming crucial in many people-centric applications, such as Social Distance regulatory compliance, Crowd Control, Building & Energy Management, Smart Cities.

Crowd behaviours are usually unpredictable, which pose many challenges for crowd counting and estimation. Other challenges may include object occlusions and real-time processing requirement.

Classical solutions to this problem can be broadly categorized as image-based and non-image-based methods.

With the latest imaging technologies, an image-based counting model estimates the crowd density by analyzing the human characteristics in high-resolution images in the pixel, texture,or object level, often achieving a superb detection accuracy.

However, sensitivity to scenario brightness, high computational costs, and privacy concerns are limiting factors that could confine the applicability of such image-based methods.
Bluewind presents here a non-image-based solution: an AI-based software platform designed to compute the number of people in indoor environment, providing real-time and accurate estimation of the crowd size.

Background

Capturing crowd dynamics (i.e., subject counting and tracking) by signal analytics in IoT networks is an emerging topic in research as well as in practical implementation of crowd management systems for smart city applications [1].

By using video footage, computer vision approaches allow accurate crowd monitoring. However, deploying a camera network is costly and inhibits scalability for events that happen infrequently. In addition, video systems have often different specific installation requirements and privacy constraints, as well.

On the other hand, supported by a large installation basis, currently available IoT devices offer an excellent instrumentation ground for crowd monitoring, thanks to the multitude of available sensors and radio interfaces (e.g., Bluetooth, WiFi, Thread and ZigBee).\ Passive crowd monitoring by wireless networks is a new emerging topic of research but some first experimental works can be found in the literature.

In reference [2], the authors proposed an algorithm to localize and count multiple targets. In order to address the non-linearity of the impact of multiple subjects on the radio signals, they proposed a successive cancellation algorithm to iteratively determine the number of subjects by modeling the indoor human trajectories as a state transition process, using an indoor human mobility model and integrating all information into a Conditional Random Field (CRF) to simultaneously localize and count the subjects. The achieved results are scientifically excellent but it's not really easy in term of deployability because of the high computational cost.

In reference [3], the authors proposed a non-image people counting system based on a Deep Neural Network (DNN) model using fine-grained physical-layer wireless signatures such as WiFi CSI (Channel State Information) data. Real test-bed experiments showed that the proposed system can achieve an average correct classification rate up to 88% when estimating the crowd size in indoor scenarios with up to nine people. The proposed system is not expensive but instead the system is not accurate with a big number of people.

In reference [4], the authors suggested a people counting algorithm using Impulse Radio Ultra-WideBand (IR-UWB) radar sensors, equipped with antennas which have narrow beam width. The system performances have been validated in a representative environment, showing results with large accuracy. However, the use of dedicated UWB radar sensors is still an expensive choice for applications in massive IoT smart spaces, where thousands of IoT devices are deployed.

Bluewind AI framework proposes the transformation of a dense MIMO WiFi network into a passive crowd sensing system by exploiting Machine Learning (ML) tools that process multi-dimensional CSI extracted from different PHY (PHYsical layer) frames, MIMO antennas and sub-carriers. Dense MIMO networks pose remarkable scalability challenges in signal processing due to the increase of the dimensions of the CSI data that are usually represented as tensors or multi-dimensional arrays.

Therefore, unlike previous approaches, Bluewind propose here ML tools that are designed to fully exploit the statistical coherence of the CSI data over this multi-dimensional space domain (i.e., antenna, frequency, time) in order to extract compact but maximally informative CSI features. In other words, CSI data tensors are preprocessed to produce custom-designed features that are organized in accordance to the meaning of the underlying data dimensionality.

Value added by Wi-Fi

Internet of Things (IoT) and new ubiquitous connectivity paradigms beyond 5G have created unprecedented dynamics for opportunistic sensing by exploiting low-cost radio devices . Such new sensing modalities leverage the cross-fertilization of computing and communication technologies and are typically achieved through the transformation of natural, stray or ambient radio frequency (RF) radiation into new sensing ways to probe the environment and the people moving inside it.

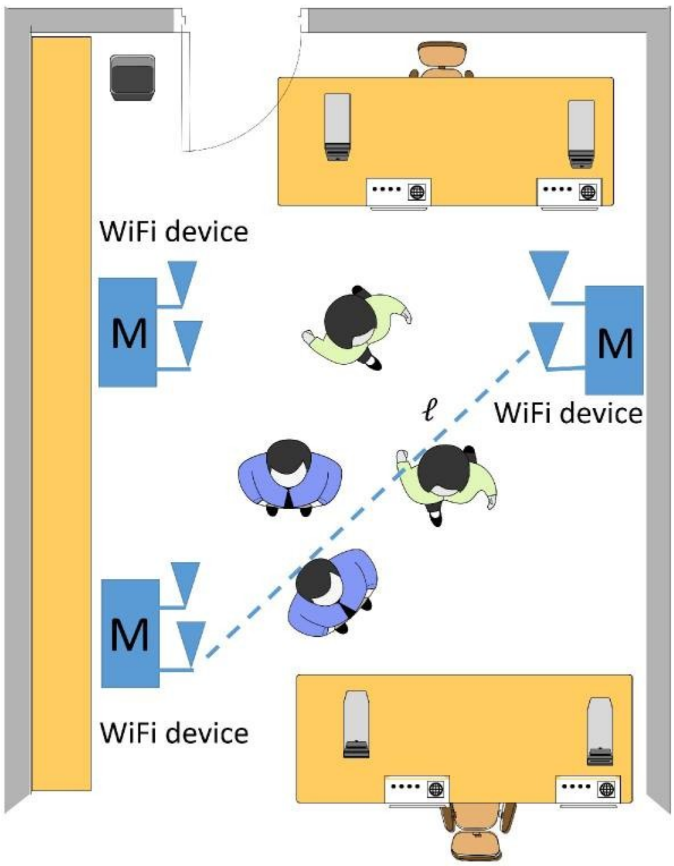
In particular, the use of devices with built-in radio modems (e.g., WiFi or cellular-enabled devices) and Multiple–Input Multiple–Output (MIMO) capabilities, as envisioned by 5G for device-free (or passive) body motion sensing , is becoming attractive in many fields. Device-free radio sensing provides privacy-preserving monitoring with increased robustness to environmental conditions with respect to video-based systems .

Compared with conventional motion detection systems using sensors, vision and radar. Wi-Fi-based systems have the advantage of being device-free, requiring no additional or specific devices to provide passive service.

For indoor settings such as homes, hospitals and office buildings, the wireless communication service is already established, and additional devices are not necessary. Therefore, motion detection systems using Wi-Fi can be implemented at a low cost.

In this work, Bluewind address the specific problem of passive people counting in an indoor space covered by a network of MIMO WiFi devices. The proposed counting system tracks and classifies the perturbations of the electromagnetic field maintained by a WiFi network to detect and discriminate multiple subjects (namely the targets) that cause such perturbations.

As depicted in the scenario of the following Figure, target detection and counting is based on real-time processing of the radio channel that is measured by a dense network of MIMO WiFi devices configured as transmitters (TXs) and receivers (RXs) according to the specific wireless protocol.



Picture 1

Channel State Information

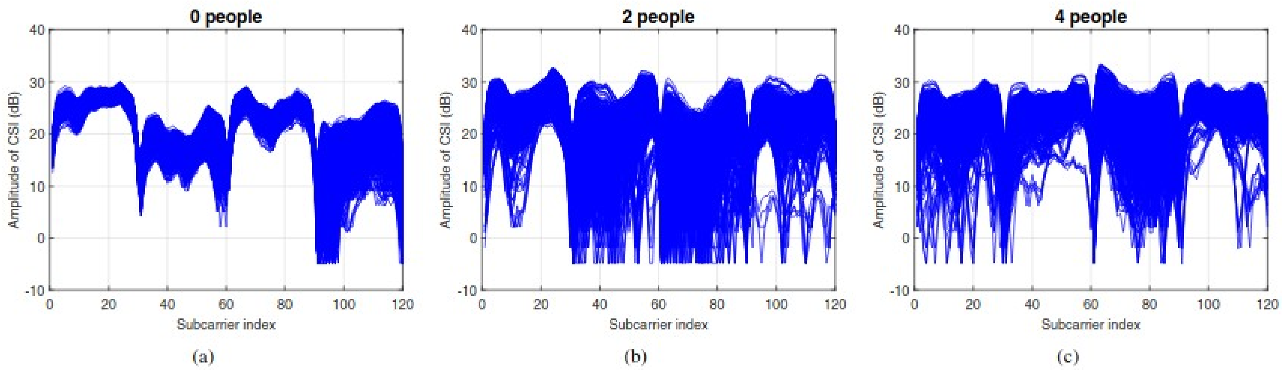
Modern WiFi devices that support IEEE 802.11n/ac standard typically consist of multiple transmit and multiple receive antennas and thus support MIMO. Each MIMO channel between each transmit-receive (TX-RX) antenna pair of a transmitter and receiver comprises of multiple sub-carriers.

These WiFi devices continuously monitor the state of the wireless channel to effectively perform transmit power allocations and rate adaptations for each individual MIMO stream such that the available capacity of the wireless channel is maximally utilized .
These devices quantify the state of the channel in terms of CSI values. The CSI values essentially characterize the Channel Frequency Response(CFR) for each sub-carrier between each transmit-receive(TX-RX) antenna pair.

CSI provides fine-grained physical-layer information, such as multipath signal components (i.e., subcarriers) with amplitude/phase information for each subcarrier, as compared to the coarse-grained RSS. CSI has recently found many applications such as localization, gesture recognition, human activities recognition, breathing and heart rates tracking during sleep, customers behavior analysis, etc.

In the application of indoor people counting, CSI profiles can potentially provide more discriminative features and are more sensitive to the number of people in the environment, without the need to install many transmitters and receivers.

In the following figure, it is possible to see the influence of the number of people on the CSI.



Picture 2

Based on these results, Bluewind chose to implement our counting system using CSI fingerprints.
Bluewind solution stands as the first device-free fingerprinting indoor counting system that purely uses CSI phase information.
It utilizes the CSI phase information extracted from simply a single link to estimate the number of targets, neither requiring the target to wear any electronic equipment nor deploying a large number of access points and monitor devices.

AI Based Method

From prior analysis, it was easy to divide WiFi sensing has three kinds of applications: activity recognition, indoor localization and human authentication. Since different human activities have different effects on WiFi signals, some simple machine learning methods can separate these known activities based on CSI.

However, using a WiFi signal to detect the number of people in a room is much more complicated because the state of the person in the room is unknown.
Bluewind was unable to separate the WiFi signal into the specified activity and further determine the number of people in the room. In other words, it was difficult to extract features that are directly related to the number of people manually.

Since it is possible to manually extract features, so there could be another way to solve this problem? May be computer vision could be an inspiration.
The researchers in computer vision use deep learning approaches to extract features automatically to get the state-of-art performances. In some specific tasks, these applications even exceed the performances of humans. Hence, it is possible to solve this problem based on neural networks.

Three reasons to believe that deep learning can solve this problem:

1. Neural network can effectively solve nonlinear classification problems
2. CSI values exhibit large variability among different sub-carriers
3. CSI values are stable at a fixed sub-carrier

Bluewind method fully utilizes the characteristics of amplitude and phase of CSI with a specifically designed CNN-LSTM network, where the CNN is applied to extract the deep features while LSTM is applied to handle time series signal.

Meanwhile, to make our model more flexible to adapt the time evolving of the crowd-counting in an online manner, it is possible to add an online learning mechanism to correct our deep learning model by fine-tune the last layer parameters of neural network.

This method with time-evolving features, thus greatly improve the practicality.

Conclusions

The proposed application task is to compute the number of people within an indoor environment.
The application is designed to output the number of individuals from different CSI data streams coming from the pre-established dense MIMO WiFi network. The actual computation is performed by a deep learning pipeline.

The main contributions of this pipeline can be summarized as follows:

- Analyze the correlation between crowd counting and the variation of CSI by utilizing deep learning to characterize this relationship. This is the first solution to solve the population of WiFi signal populations using neural networks. It proposes a new approach to solving such problems.
- Adopt a deep learning approach to solve multi-person context awareness problems. Using LSTM and CNN to implement automatic extraction of features. Using a softmax layer for crowd counting.
- To further improve the performance of the counting system, add an online learning mechanism to the activity recognition model. The experiments show that by this mechanism is possible to reach the 90% accuracy.
- Adding some simple and effective denoising methods that eliminate noise while maximizing the characteristics of the data.

The proposed architecture can also be extended to localize individuals within indoor settings, since, in the area covered with WiFi, human movements may cause observable variations of WiFi signals.
By analyzing the CSI fingerprint patterns and modelling the dependency between CSI fingerprints and locations through deep neural networks, the proposed method is able to estimate the objects' locations according to the measured CSI fingerprints through DNN regression.
Bluewind solution stands as a real case example of embedded data-driven counting system. It involves a machine learning approach and demonstrates how data-driven approaches meet the challenge of reaching high accuracy while being light and computationally efficient.

About Bluewind

Bluewind, an independent engineering company, provides world-class products, engineering and software solutions in the domains of electronics, safety critical applications, and connected devices.
As a qualified researcher for Artificial Intelligence technologies, Bluewind is actively involved in designing next generation products in the Automotive, Industrial and Medical industries.

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