Università Politecnica delle Marche
Scuola di Dottorato di Ricerca in Scienze dell'Ingegneria
Curriculum in Ingegneria Informatica, Gestionale e dell'Automazione

Machine vision and IoT applications in intelligent retail environments

Ph.D. Dissertation of:
Marco Contigiani

Advisor:
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XV edition - new series

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The problem is not having good ideas,
but is to keep believing

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Take stock of an intense period like that of a PhD period is never an easy task. These three years have been rich in terms of experiences and opportunities for my own growth. I had the opportunity to do research in a challenging sector such as the customer behaviour analysis in retail environments not only in the university context but also with the collaboration of the Grottini Lab company. The technology transfer between universities and industry it is not only important for the technological advancement but also to make local company more competitive and I am proud to have contributed to this purpose.

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Marco Contigiani

Abstract

In the retail sector, in recent years, has grown the need to acquire information about customer behavior. This information allows to optimize stores, improve the commercial offer, innovate products and maximize profits by monitoring in real time the behavior and choices of customers. The physical sales point is now no longer the only place where the purchase takes place and for this reason should be able to rapidly align with the needs of customers transforming the spaces and the shopping experience using the data collected. This aim can be achieved through the use of IoT solutions based on machine vision, indoor tracking systems and distributed sensors for environmental parameters monitoring.

In this context the research activity had as its main focus the study and development of solutions based on RGB-D cameras, WiFi smart camera for planogram maintenance, UWB indoor tracking systems and the analysis of distributed networks of capacitive sensors placed inside floor for human movement control. The effectiveness of these measuring systems and the analysis software developed have allowed to realize a complete monitoring system for retail environments that thanks to IoT communication protocols allows to analyze in detail and in real time in a store: how many people, how they move, how interact, what they buy and how long it takes to perform each of the above actions.

The research path has been conducted in full collaboration and cooperation with the Grottini Lab company. Through this synergy several installations have been made in real stores that have allowed to test the validity of technological solutions designed and at the same time to collect many data useful for the behavior analys of individual and groups of customers.

The data produced with these analysis systems are collected on IoT cloud platforms and once stored, can be processed and made visible in appropriate dashboards in terms of charts and key performance indicator to make a careful analysis of the human behavior in a retail space. In this thesis it is also mentioned the topic of interpretation of the data, crucial aspect for a correct understanding and right use of results.

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Chapter 1

Introduction

Collect data to know your customer and study its behavior: this has always been a crucial aspect for the retail industry and in recent years this need has become increasingly important. The increase in marketing tools and platforms of selling has forced retailers to transform the purchase into a marketing experience. And in this scenario the spaces play an essential role. There is the need to design stores, products and methods of presentation so that to engage and capture the attention of a customer, by now all too overstimulated. Know your customer, his behavior and his reactions is decisive to optimize space, maximize profits and increase recognition of brand and products.

The technology in this sense plays an essential role. The audit, interviews in the stores and the analysis of sales are not sufficient to learn about trends and behaviors. The use of real-time analytics tools offers the opportunity to study quickly and effectively the customer. In this work will be presented different technological solutions that allow to monitor the behavior of customers in front of the showcases, the interactions with the shelves and know its movements inside the store together with dwell times and most visited areas.

The use of machine vision techniques, image processing, indoor tracking systems and proximity detection are currently the most interesting solutions to analyze the human behavior within the space and in front of points of interest. In particular will be presented a video analysis software, referred to as Shopper Analytics, based on the use of RGB-D camera able to process the types of interactions that customers have with the products, dwell times in front of the shelves and the number of visitors. Will be also presented an embedded vision sensor IoT network for planogram maintenance in retail environments able to analyze the correct placement of products on the shelf.

About the analysis of the use of space will be presented two solutions, the first which makes use of distributed capacitive sensors immersed within the floor capable of locating persons and objects and the second that makes use of a UWB realtime indoor tracking system useful for the study of people's flows, most visited areas and dwell time spent in a store.

The measurement solutions that will be described use all the same IoT approach. After collecting data from the real context analysis each system sends the information to a cloud platform that stores and process the data. Finally will be discussed, although in not exhaustive way, about the data elaboration and presentation in terms of meaningful key performance indicators (KPI) useful to extract descriptive information about the store's performance, products, planograms used, marketing campaigns, positioning of products within the store and points of interest.

This last aspect certainly opens up new research areas to continue in the handling and optimization of data. The Ph.D program and then the work presented in this thesis has been possible thanks to the collaboration with the company Grottini Lab tha has co-financed the scholarship. The company develops high-tech solutions to measure the customer behaviour and improve the stores performance. This collaboration made it possible to carry out several demo installations at first in the showroom then in real stores with the cooperation with some partners, which have allowed to validate in a real context the developed solutions and especially test the reliability of the hardware apparatus and software used. The collected results, as we shall see in this work, are very interesting, confirming the validity of technological solutions analyzed and the potential that these can have in real use cases.

In summary, main contributions and results are about:

- RGBD not invasive technological solutions useful to acquire the customer behavior in front of the shelf;
- innovative IoT solutions able to study the planogram integrity and implement an indoor tracking system using the UWB technology;
- a smart floor implementation able to locate persons and objects in retail environments;
- the techniques to collect, process and present data and results in terms of meaningful key performance indicators and dashboards.

Chapter 2

State of the art

In the last years, the analysis of the human behavior has been of high interest to researchers because its important and different applications, such as: video surveillance, ambient assisted living, analysis of consumer's behavior, group interactions, indoor tracking and many others. In particular, in the field of intelligent retail environments, several studies to investigate how shoppers behave inside a store and how businesses can change strategies to improve sales are emerging.

The technological solutions currently used to analyze the human behavior within spaces in particular in retail environment are based on the use of computer vision and image processing, RF indoor tracking systems (WiFi, BLE and RFID), proximity solutions such as beacons BLE, distributed and interconnected sensor networks to monitor environmental parameters. In this context the solutions adopted to implement a retail store's life analysis and which are the main topics of this work can be grouped in three different technological application fields: machine vision, capacitive distributed sensors for localization of objects and people and RF indoor tracking systems.

All these solutions have in common the use of the IoT paradigm. The devices measure several environment parameters and are able to collect and send data to the same cloud platform. The data are stored and subsequently elaborated with a big data approach to study and analyze in detail the information collected. In the next few paragraphs will be presented the state of art about IoT, the technological solutions developed to monitoring the human behavior in retail environments and also will be presented a short explanation of the importance of customer behaviour analysis to study the retail environments performances.

2.1 Customer behavior and retail environments

The necessity to associate marketing retail and consumer behavior is born from the need to develop theories, strategies and management models compatible with customer behavior. The concept of shop is changed during years becoming not only the place where customers go to buy a specific product, but also the place where the customers go to spend part of their time. Therefore, it is very important to study the consumer behavior so as to investigate the elements of the decision-making process of purchase that determines a particular choice of consumers and how the marketing strategies can influence the customer.

Empirical researches on consumer behavior are primarily based on the cognitive approach, which allows to predict and define possible actions that lead to the conclusion and to suggest implications for communication strategies and marketing. The basic principle of this approach is that individual actions are the result of information processing. The person collects the information, interprets, processes and uses them to take action. Cognitive approaches cannot completely explain the complexity of consumer behavior, which lives in a changing social and cultural context.

According to this approach, the choice of purchasing comes from the ability of the products to generate specific sensations, images and emotions. According Perreau [3], five are the steps of consumer buying decision process:

1. Perception of the problem: the shopper recognizes a gap between the current situation and desirable situation, therefore perceives a need. The need can be described as a genuine request that comes from the inside and the satisfaction of which is necessary for the survival or to maintain a good level of psychophysical balance.

2. Research of information: in order to identify the satisfying solution for the perceived need, the consumer searches for knowledge in the memory, or if the information possessed by the individual is not sufficient, will seek additional data from external sources.

3. Evaluation of options: consists of selecting one of the available alternatives based on the criteria defined in the previous step.

4. Buying decision: after having identified the place and time.

5. Post purchase behavior: is the adequacy of the product purchased and thus the level of consumer satisfaction.

Therefore, the marketing retail discipline defines the set of marketing strategies to point of sale oriented so as to attract the customer and to increase the activities of businesses. To achieve its objectives, the retail marketing uses many techniques through several stages of planning by developing a marketing model for the shop-customer using the most important techniques, in the following described:

- Visual merchandising is the activity of developing floor plans in order to maximize sales. The purpose is to attract, engage and motivate the shopper towards making a purchase. As means of visual merchandising is often widely used a planogram [4].

- Pricing is the activity of establishing the best price that is competitive for shoppers and at the same time with a good profit margin for the store.
- Sensory marketing, to make the shopping experience more pleasant and exciting for the client.
- Loyalty tools, to encourage the consumer to return to the store and to make new purchases.
- Non-conventional marketing concerns original ideas to push the customer to come into the store and trigger a word of mouth process. The best way to know the behavior of the customer is to create an automatic system that, on the base of acquired knowledge, can predict the purchase of many products and also choices.

Literature and real cases demonstrate how pervasive computing enhance benefits for retail; this is true for consumer as well as for retailers [5]. In the last decade we observed a turnaround in the concept of shop. One time it was only the place for searching and buying products, nowadays it has become the place where consumers spend time, test products in real time or just inquire about the recent technological products or trends. New stores make are places where many people still prefer to visit and spend time stores. People's shopping is guided not only by the prices, but also by the ambiance of shopping, professional consultation, seeing, touching and trying the products [6]. Because of this, researches over consumers behaviour are strictly related with in-store features for the retailers. The study of consumers behaviour is needful for many aspects. First of all to investigate over the decision-making process which drive consumer towards choices, different from one another; furthermore, it is the only, a not empirical way to evaluate the success of marketing strategies.

Technology provides analytics taken from consumer interaction with spaces; it can give many information about customers, allowing the retailer to customize the shop to their needs and adapting product arrangements, expositions, design according to their behaviours. Data extracted in this way are objective; indeed, this kind of decision-making process is lead to an objective and reliable data collection. Intellectual approaches are not able to explain the complexity of consumer behaviours, because they arise from many aspects such as cultural context, habits and so on. Several aspects of these problems are currently solved using artificial intelligence and, in particular, vision [7]. Previous works demonstrate as the growing complexity of retail surroundings makes essential the presence of ambient intelligence to augment the environment intelligent, aimed to the awareness of human presence.

2.2 The IoT approach

The term Internet of Things was introduced by Ashton [8] in the supply chain management field. Successively, mainly in the last years this term is related to several applications transportation and logistics, healthcare, smart environments, personal and social domains [9].

Taking into account the work of [10], IoT can be realized thorough three paradigms: internet-oriented (middleware), things-oriented (sensors) and semantic-oriented (knowledge). Taking into account the work of [11], eight are the key components that IoT have to support:

1. Devices heterogeneity: smart objects are different from the computational and communication viewpoint, so the management of these different devices occurs at architectural and protocol level.

2. Scalability: different objects are connected to a global infrastructure, so problem of scalability happen on different levels (name and address, data communication and network, information and knowledge management and service provisioning and management).

3. Ubiquitous data exchange through proximity wireless technologies [12].

4. Energy optimized solutions so that the need to have solutions directed to reduce the energy used for communication and computing purposes is recently more attractive.

5. Localization and tracking abilities so that smart objects are localized and tracked in their movement in physical environments. This occurs in applications that widely adopt RFID technologies.

6. Self-organizing abilities for which in order to reduce the human intervention in a dynamic scenario where smart objects must autonomously react and organize themselves [13], [14].

7. Semantic interoperability and data management for which IoT will exchange and analyse a huge amounts of data and so from the point of view of interoperability among several applications have to provide data with adequate and standardized formats.

8. Embedded security and privacy-preserving mechanisms, so IoT technology has to be secure and privacy-preserving by design. So that security must be considered a key system-level feature, and considered in the design of architectures and methods for IoT solutions.

Moreover, there are three components required for IoT [15]: hardware (sensors, actuators and embedded communication hardware), middleware (on demand storage and computing tools) and presentation (novel visualization and interpretation tools useful for different platforms and applications).

IoT shares many characteristic with Ambient Intelligence [16]. The concepts of Ambient Intelligence (AmI) [17], [18] provide a vision of the information society in which the emphasis is on a greater attention to the user, more efficient support services, enrichment opportunities for the user, and an increased support for human interactions.

People are surrounded by intelligent and intuitive interfaces, integrated in every kind of object and an environment that is capable of recognizing and responding to the presence of different individuals in a fluid, most intrusive and often invisible scenario [19]. The characteristics of a smart environment,in accordance with the users that use it, should be in general those listed below: not intrusive, personalized, adaptive and predictive.

As previously said, many and different are the applications domain of IoT models. They can be categorized into four applications domains: transportation and logistics, healthcare, smart environments, personal and social [10] [20]. Vehicles such bicycle, cars, buses, and trains are equipped with sensors, actuators, and processing power, in order to optimize their performances but also are able to provide important information concerning, for example the traffic control, the monitoring of the status of the transportation, the knowledge of the better navigation and route. Other examples involve collision avoidance systems and also monitoring of transportation of dangerous materials. Moreover, augmented maps can be another service that provides useful information about the area of interests for users [21].

Several are IoT technologies used for healthcare applications: they can be grouped basing on their use and their application fields. For example: tracking and monitoring people to evaluate their state of health, detection and authentication of people for their security and safety, automatic data collection and enabling function centred on patients, that provide in real-time information on the health of patients [22].

Smart environments domain is particularly important for IoT scenario, as it represents the link between the individual (citizen, consumer) and the overlying layers of adoption of IoT paradigm (Smart City, Smart Grid). Small dimensions sensors and actuators distributed in office, home, industrial plants are able to make life more comfortable considering different aspects: room lighting can change according to our preferences and weather conditions, energy can be automatically preserved, room heating can adapt to match the individual preferences.

In personal and social domain, IoT applications aim to make easy the communication between people ensuring a continuous interaction and automatic sending of messages to friends to maintain and build social relationships [23].

There are futuristic applications that are based on technologies that are still to come and the implementation is too complex. However, an important open problem and actually object of study is the standardization activity on different IoT technologies, in fact there are several contributions towards this direction.

2.3 Fields of application

In order to satisfy the need to measure the customer behavior and the store performance have been developed four different solutions. The first uses an RGB-D camera for monitoring the customers behaviour in front of shelves and showcases. The second solution implements an analysis of the planogram to continuously verify the correct location of products on shelf. The third solution uses an innovative intelligent smart floor equipped with capacitive distribuited sensors and self powered with energy harvesting techniques for localization of objects and people. The fourth and last solution makes use of an indoor UWB tracking system for tracking customer movement within the retail space. In the next paragraphs will be presented in detail the state of art of the technological fields where this new solutions are collocated: machine vision, smart floor and indoor tracking system.

2.3.1 Machine vision

In recent years, the visual analysis of dynamic scenes is one of the most important research activities in computer vision and image understanding. When the visual analysis concerns moving scenes, the general method includes following steps: modelling of environments, motion detection, human identification, classification of moving objects, tracking, behavior understanding and data fusion from multiple cameras [24–26].

In this work, we focus the attention on:

- the analysis of the planogram mantainance and the correcto location of products on shelf;
- the study of the consumer behavior in a real retail store, in order to recognize human actions [27–30], such as interacting with the shelf, picking or releasing a product, moving in a group, and knowing most visited areas in the store.

Consumers are main actors in the project because the goal is to increase their satisfaction and, therefore, enhance their purchases. Currently, the identification of the shoppers behavior implements systems of human observation or video recording with traditional cameras. Some tools, such as virtual stores or eye tracking provide incomplete and unrepresentative data because they are based on a small sample of buyers. As a result, by univocally identifying shoppers and automatically analysing their interactions with the products on the shelves and their activities in different zones, our design considerably increases the value of the current marketing research methodologies.

Moreover, the main innovation concerns the original use of tracking system, and the other interesting point concerns the real experimental platform described in the results section combined with a vision based statistical approach. Therefore, the solution developed aims to propose an intelligent low-cost embedded system able to univocally identify customers, to analyse behaviors and interactions of shoppers and to provide a large amount of data on which to perform statistics.

The automatic extraction of features that univocally recognize each subject in the scene and their movements, provides an important tool to identify important operations concerning marketing strategies. The application implements techniques of image processing such as: background subtraction, low-level segmentation, tracking and finding contours, in order to map a single shopper and/or a group of people within the store that interact with the products on the shelves, defining an ID unique to each visitor filmed by the camera, and classifying these interactions.

The customer behavior in front of shelf have also a crucial correlation with the location of products on shelf and the planogram manteinance. The planogram is a detailed visual map of the products in the store indicating the position of the products in order to supply their best location for suppliers. Planogram attempts to capture the absolute physical positions of an assortment, the relative locations of products in an assortment, the amount of space allocated to each category and each type of stocking keeping unit (SKU) within the category. In other words, the planogram is designed for reasons such as increasing sales and profits, introducing a new item, supporting a new merchandising approach, etc. Deviating from the planogram defeats the purpose of any of these goals.

A study of the National Association for Retailing Merchandising Services (NARMS) found that a 100% planogram compliance after an initial reset, within two weeks yields a sale lift of 7,8% and a profit improvement of 8,1% [31,32]. A fundamental aspect is the development of a shelf planogram to reflect the real need of the product in that particular location and in that time-frame. Compliance with planogram is crucial to avoid stock-outs and to maintain the expected level of sell-out; an estimate indicates that a 10% of planogram errors leads to an increase of the 1% in stock-outs and consequently decreases the sell-out of the 0.5%.

In the literature there are many studies working on the analysis of planograms, e.g., [7, 31, 33]. In particular they demonstrate that planogram maintenance is a key aspect to increase shelf value and improve sell out. A series of patents for determination of inventory conditions, determination of product display parameters, planogram extraction and detection of stock out conditions based on image processing can also be found in [34–37]. At the base of these products there are algorithms able to detect and extract several features such as logo [38] or books [39]. In [40] and [41], it is possible to retrieve examples of software that use images for automatic planograms compliance and generation. Both are commercial products that are based on images manually collected in front of the shelf and analyzed on a web based platform or in a local desktop application. Differently from our system they are not real time and also they are always managed by a man using a camera, and for this reason they are not monitoring the planogram continuously. This aspect is important not only to continuously verify the planogram maintenance, but it is also essential for the Shelf-Out-Of-Stock (SOOS) management system based on real time sensor based measures and for costumer's activity recognition on the shelf interaction. In fact, the same system architecture has been extensively used to monitor both the behaviour of the costumers in front of the shelf [42–46] and the absence of products on the shelves [47].

In this work, to protect the integrity of the planogram, we propose an embedded system, mainly based on a WiFi smart camera installed in points considered strategic for the stores taken into consideration. Each embedded system produces an amount of information useful not only to assess the integrity of planogram, but also concerning out-of-stock.

2.3.2 Smart floor for user localization

The development of a floor that enables user localization and also allow to analize movement of users in space applications is an interesting topic. In the literature there are different solutions to implement a smart floor; most of them are based on a pressure sensing system.

The MIT Magic Carpet [48–50] created by MIT Media Lab and the University of Limerick Ireland uses piezoelectric wires and optical proximity sensors. This system is characterized by a large sensing area and frame rate but presents poor sensor densities. This interactive environment uses a pair of Doppler radars to measure upper-body kinematics, i.e. speed, direction of motion, amount of motion and a grid of a PVDF piezoelectric wires hidden under a foot carpet to monitor dynamic foot position and pressure. The aim of this system is an audio application: the user modifies and transforms complex musical sounds and sequences while they are moving on the carpet.

The ORL Active Floor [51] designed by Oracle Research Lab uses load cells that provide little detail and cannot be used for high sensor densities. An array of sensors provides information on the distribution of a vertical ground

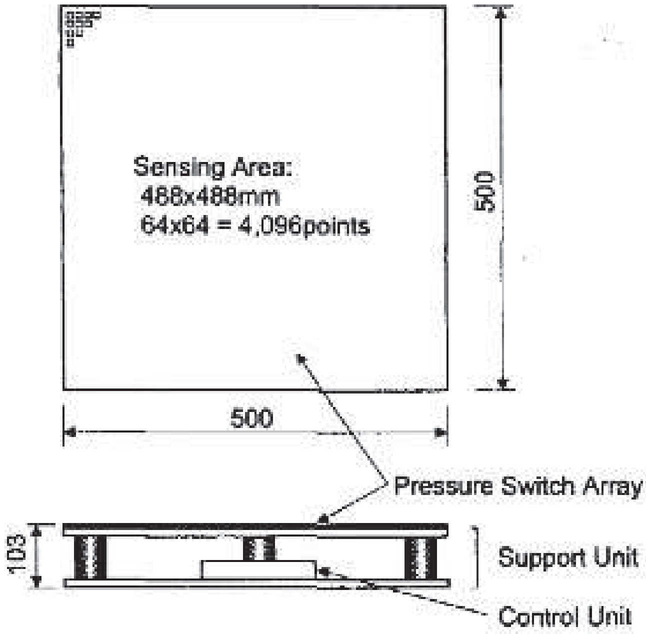


Figure 2.1: The structure of the sensor floor unit [1].

reaction force over the area of the floor. When only one object is in contact with the floor, its center of pressure is known. There is a problem when two or more objects are in contact with the floor since, it is not possible to determine without ambiguity the centers of pressure for the objects, departing from the sensor array readings. This aspect was a subject of research at ORL.

The University of Tokyo, Japan, created a high resolution pressure sensor distributed floor [1] that can simultaneously detect both human and robots. This distinction is possible thanks to the high resolution of the floor, and its modular structure allowed an easy application to a real room. The authors retain that the sensor floor system can be used to understand the behaviour of humans in a room, and that it will also play an essential role in the future human-robot symbiosis environment by detecting the position and direction of humans and robots in the room. Figure 2.1 represents the sensor floor unit consisting of three parts. The sensor floor has a number of sensor units: for example 16 sensor floor units arranged in 4x4 array.

Another sensor system is the Z-Tiles [52, 53] designed by the University of Limerick Ireland and MIT Media Lab. It uses a force sensitive resistor technology. This system has the advantage of having a modular design, a series of prototype Z-tiles nodes join together to form a flexible, pixellated, pressure sensing surface, a high frame rate, but a low sensor density. This surface provides full time-varying, force-distribution information, since the Z-tile nodes form a self-organising network to allow for easy data extraction from the floor,

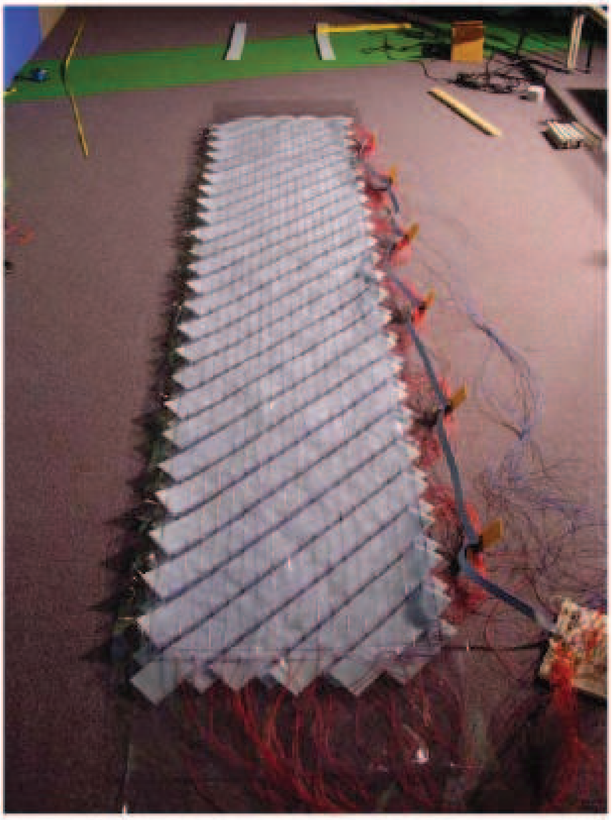


Figure 2.2: The prototype sensor mat with 4 grids and 2 layers [2].

without restricting the size or shape of the floorspace. The applications of this structure concern generating music from the movements of dancers, as an input device for the control of computer games, and so for virtual reality applications.

The Floor Sensor System [2], a solution of the University of Southampton in UK, uses a binary switch technology, with the advantage of a low cost design, but providing poor data useful for tracking and localizing users. In this work a prototype system for acquisition of footfall data has presented, designed to study the gait by applying an alternate modality. The system consists of three main components: a large sensor mat, showed in figure 2.2, a hardware interface, and software. The sensor system is a promising prototype.

The projects AME floor I, AME floor II and AME floor III [54] developed by the Arizona State University are based on force sensitive resistor technology. They have a temporal domain, but not spatial domain. The pressure sensing floor system has a higher frame rate, less latency, high sensor resolution, large sensing area useful with real time data to know the location and amount of pressure exerted on the floor. The floor has been integrated and synchronized with the marker based motion capture system to create a smart environment for movement based human computer interaction. The sensing system has been used to drive a gesture recognition system that uses both kinematics and pressure distribution to recognize gestures. These gestures could have similar body shapes but different weight distribution, so pressure sensing is fundamental to distinguish between such gestures. The ability to read and analyze both body kinematics and pressure distributions suggests users to communicate with computers. A problem of AME Floor-III is that now is not portable, and so interfacing is one of the problem that must be solved.

2.3.3 Indoor tracking system

In a localization system, several are the performance criteria that can be classified in different areas [55]. One is accuracy, determined as the mean error distance between the estimated location and the real location, and for a positioning system is the most important requirement. A high value of accuracy corresponds to better performances for a localization system. Responsiveness is another requirement that indicates how quickly the position of a moving object is updated. The updating must be fast for a quickly moving target. The problem of coverage (local, scalable and global) is strictly related to the accuracy and represents the network coverage for a specific area. This parameter is important to evaluate the performances of a positioning system and establish the size of the affected region. Other important parameter is the adaptiveness that indicates the ability of the localization system to adapt to environmental changes. This system appears efficient if it is able to provide a correct positioning without a calibration even if some differences in the environment occurs. Scalability is another important parameter when a system is designed since it means that the system can operate with a larger requests of location and a larger coverage. A scalable system must be able to easily manage a high number of variables. Also cost and complexity influence the performances of positioning systems since the complexity of algorithms and signal processing used to estimate the position represents another problem that must be considered. The complexity and accuracy are requirements that can significantly influence the overall cost of the system.

Taking into account the study conducted in 2008 by the National Institute of Standards and Technology (NIST)[1], the most important characteristics that a positioning system must have can be synthesized as follows: positioning precision near 1 meter; functioning on all buildings; no training required on site; stability against structural changes; and limited costs.

In the work of [56], the authors summarize the main general problems and requirements for indoor tracking systems taking into account several environments and locations. Basing on this study they classify the positioning systems technique according to their use. In the last recent years, many technologies to

[1]www.nist.gov, last accessed: March 7, 2016

detect indoor localization have been proposed: they include Global positioning system (GPS), Radio-Frequency IDentification (RFID), cellular based, WLAN based, Bluetooth, Ultra Wide Band (UWB) and many more [57].

GPS is one of the most successful positioning system in outdoor environments. However, one of the main problems of this technology is that it can not be used in many indoor environments due to the lack of GPS signal and also the hardware is quite expensive [58]. GPS is not efficient also in urban canyons, where the calculation of position is not univocally determined and the signal can be absent.

Radio-Frequency IDentification (RFID) is a technology used to store and retrieve data using an electromagnetic transmission to an RF compatible integrated circuit and actually is considered as a tool to increase processes of data handling. This kind of system has many basic components and it can be passive or active [57].

Also cellular-based systems are mainly used to estimate user location for outdoor applications. The accuracy of the method is generally very low and depends on the cell size. Moreover, for indoor positioning systems this technology is possible if the building has several base stations or one base station with strong RSS signal received by indoor mobile clients.

Wireless Local Area Network (WLAN) become a very popular technology in public hotspots and corporate locations mainly in the last years. In localization applications where the accuracy is a very important requirement this technology is not adapted since typical WLAN positioning systems using RSS is about 3 to 30 m, with an updating rate in the range of few seconds.

Bluetooth technology compared to WLAN has a gross bit rate lower and also the range is shorter. However, Bluetooth is in most phones and personal digital assistants (PDAs) and supports many different networking services. Each device has a unique ID. To use Bluetooth technology is necessary that all devices have Bluetooth actives, and not always this occurs.

The last technology is UWB used in this work. UWB is a radio technology for shortrange (< 1 ns), high-bandwidth communication with a low duty cycle and has the properties of multipath resistance. In [59] have been presented the advantages of this technology. Compared to RFID systems, which use on single bands of radio spectrum, UWB simultaneously transmit signals on multiple bands of frequencies (from 3.1 to 10.6 GHz). Unlike RFID, UWB signals are transmitted with a shorter duration, consuming less power and can operate in a wider area of the radio spectrum. UWB and RFID can operate in the same area without interference thanks to the differences in signal types and radio spectrum. Moreover, UWB signal is able to pass through walls, devices and clothes with no interferences.

UWB technology has high values of indoor location accuracy near to 20

	WiFi	BLE	RFID	UWB
Precision	5-20mt	1-5mt	50cm-1mt	15-30cm
Costs	Medium	Low	High	Medium
Battery life	Low	High	High	High
Installation complexity	High	High	Low	Medium

Table 2.1: Main differences between different indoor tracking technologies

cm not achievable using conventional wireless applications (RFID, WLAN and others), and so it is very useful for applications that require a high levels of precision in real time for 2-D and 3-D localization. UWB radio signals are employed for indoor location and tracking [60]. Positioning systems can be divided in three main categories: time-of-arrival, direction-of-arrival and signal-strength based systems. Identifying the position of a target in a wireless system involves the set of location information from radio signals that travel between the target and a number of reference nodes. In table 2.3.3 have been synthesized the main differences between the different indoor tracking technologies in terms of cost, battery life, installation complexity and precision. For this purpose, time-based positioning technique measure travel times of signals among nodes and UWB technology represents a very useful means for wireless positioning for its high resolution in the time domain.

Chapter 3

Technical solutions

In this chapter will be presented the technological solutions developed in this work, figure 3.1. Initially will be described Shopper Analytics a software for the analysis of customer behavior in front of the shelf together with a description of the tests carried out in Grottini Lab showroom and in real stores. Subsequently will be presented an IoT smart camera to analyze the planogram maintenance and the location of products on shelf. Afterwards will be shown a smart floor implementation and the tests made for the validation of the technological choice with an analysis of possible applications in the retail environment. Finally, will be presented the UWB system for tracking of trolleys and baskets in stores. In this last section after a short description of the technology will be analyzed in detail the tests and system performance in real environments in particular in the retail environment. The next chapter will present the first case of simultaneous application in a real store of Shopper Analytics and UWB tracking system, explaining in detail the techniques used to merge data collected by the two systems and the initial results obtained in terms of reliability.

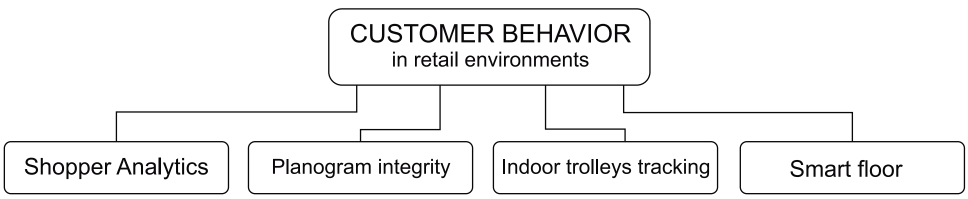


Figure 3.1: Technological solutions developed for the customer behavior analysis.

3.1 Shopper Analytics

The software Shopper Analytics, as already anticipated, using a RGB-D camera is able to analyze and process interactions and number of visitors in front of areas of interest as exhibition areas, shelves and showcases. The camera placed above from these areas can extract relevant data as dwell times, types of interaction sending in real time the data to a server cloud for the collection and storage. The software has been developed in collaboration with PhD student Daniele Liciotti, the VRAI university research team and the company Grottini Lab.

3.1.1 System architecture and method

In order to satisfy both functional and non-functional requirements of the system, a Single Board Computer (for example an Asus Vivo mini pc) has been used, since it is sufficiently small and suited to manage all functions. Functional requirements are: counting and classification of people, their interaction with the shelf, sending data to web server and data analysis; while non-functional requirements are: place of installation and connection modes. As RGB-D sensor, Asus Xtion Pro live has been chosen due to its smaller dimensions than Microsoft Kinect, and the power supply is provided only by USB port. It does not need an additional power. Figure 3.2 shows the general scheme of the implemented system and the interactions between the components. The system consists of three devices, listed below:

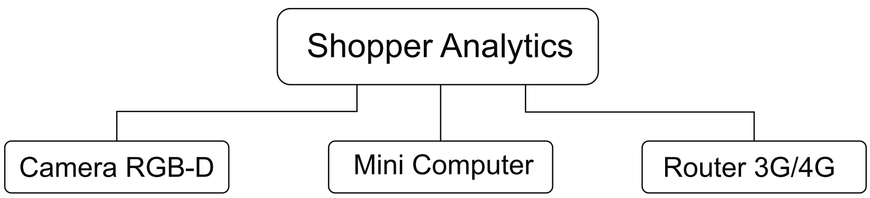


Figure 3.2: General scheme of the implemented system.

- Single Board Computer: is a complete computer built on a single circuit board, with microprocessor(s), memory, input/output (I/O) and other features required of a functional computer. Single-board computers were made as demonstration or development systems, for educational systems, or for use as embedded computer controllers.

- Asus Xtion Pro live: is composed by an infrared sensor, a RGB sensor and 2 microphones. It is able to provide in output a RGB representation of the scene and also allows to reconstruct a depth map of the same.

In the depth map the value of each pixel codifies the distance of each element from 3D scene.

- Router 3G/4G Wireless. Debian operating system is installed allowing an easy configuration of RGB-D sensor of Asus Xtion Pro Live compiling following modules: OpenNI Library and PrimeSense Sensor Driver.

The RGB-D sensor, figure 3.3 is installed in a top view configuration at three meters of height from the floor. It visualizes a maximum area (shopper tracking area) of 1.8m x 3.2m, but the shelf area (shelf tracking area), that has a height of two meters, results smaller than this. The system implements the algorithm that calculates the interactions map between the people in the store and the shelf, sending successively data to a database. Trough a PC, it is possible to connect a smartphone to the database and to visualize the state of system and other interesting information.

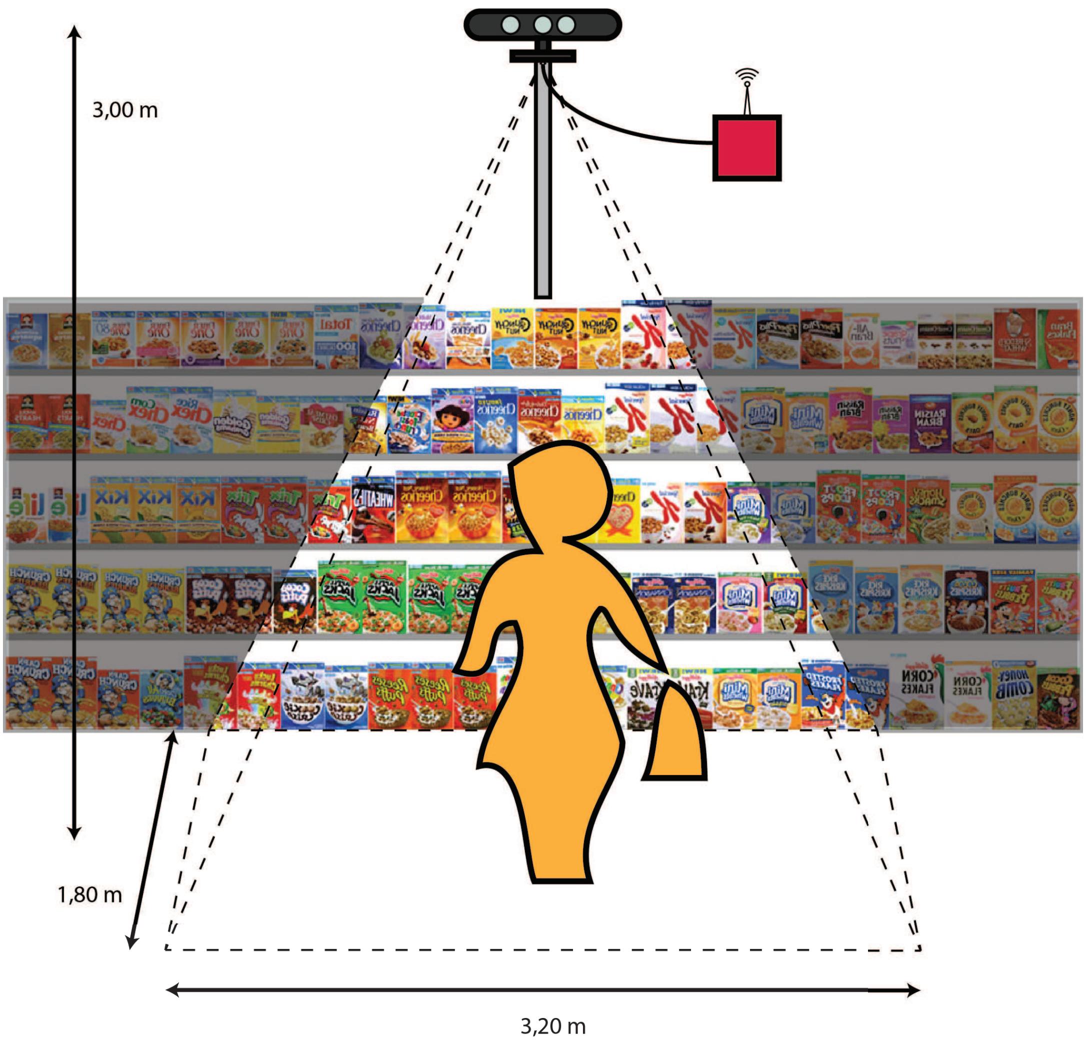


Figure 3.3: Environment of system installation.

Figure 3.4 represents the block diagram that identifies the main steps of the algorithm. The input is the image detected by the camera and the output is the typology of interaction between the user and the products on the shelf.

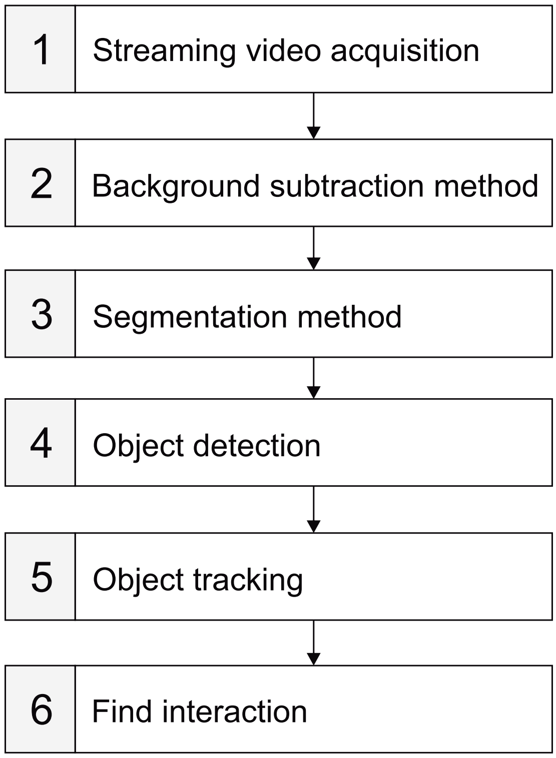


Figure 3.4: Logical steps of the implemented algorithm.

In the first step, the system acquired the streaming video from the RGB-D sensor. After this, the background subtraction method is implemented, that is one of the most commonly used algorithms for detection of moving objects within a sequence of images. This approach is reliable since each pixel also maintains the depth information, that is not available with a RGB image and so it allows to detect the distance of each blob. Moreover, in order to avoid false detection of objects (false positives), the background image is dynamically updated. After the background subtraction, a threshold value is defined that allows to discriminate positive signals that indicate moving objects, by false positives due to background noise, this method is called segmentation. Another important step consists of the object detection where, for each significant blob, the boundary and the maxima points are found, corresponding to the head of the person. If these points are surrounded by a region of the lowest points comparable to jump head-shoulder of a human then is a valid blob. The next phase is the object tracking that recognizes the pathways of different blobs along the frames. In other words, in this phase, each blob is recognized and tracked within the streaming video. For each person, the height is determined verifying that this is in the neighborhood of the height of the person in the previous frame.

This method is easy but very effective since it is based on the depth image; moreover it is not subject to rapid changes in the forms, allowing a good and reliable tracking. Figure 3.5 shows how the people are tracked between two successive frames (frame i-1 and frame i). In both frames, the same identifier (ID1) detects the same blob, tracked between frames, so each identifier univocally identifies a person. In this phase of the work, users are not tracked across the sensors, but we retain that this approach must be investigated in future, so that to each visitors maintains a ID unique during the entire visit to the store implementing a re-identification algoritm.

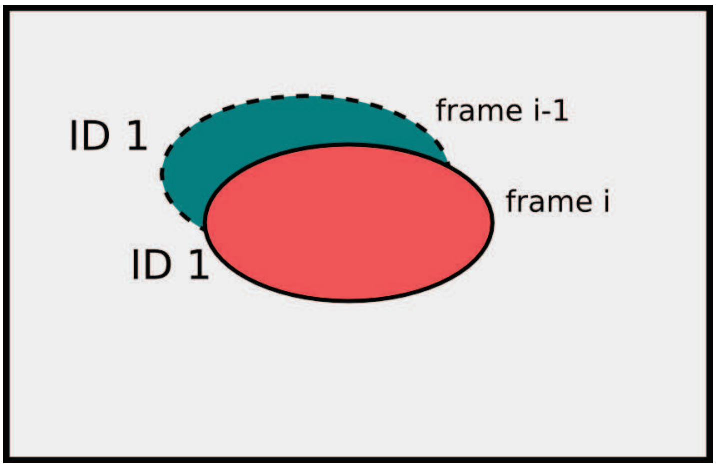


Figure 3.5: Object tracking implementation.

The last step of the algorithm provides the find interactions procedure. When a person has a contact with the shelf, the associate blob is inside the shelf zone. Then, it is possible to detect the exact point of contact by means the definition of common 3-dimensional (XYZ) system coordinates. The shelf zone, that is defined by user in a configuration file, is formed by three parameters (x shelf dist sx, x shelf dist dx and y shelf dist) as also showed in the following figure 3.6. When the people interact with the shelf can be presented three different situations, classified as follows:

1. Positive: when the product is picked up from the shelf.

2. Negative: when the product is taken and then repositioned on the shelf.

3. Neutral : if the hand exceeds the threshold without taking anything.

Figure 3.6: Setting parameters of the shelf zone.

The template matching method has been used to identify and to classify the interactions between the people and the shelf. So, when there is the first contact, the position of the hand in the RGB image is saved, and the same operation occurs when the interaction ends, in order to compare the first image and the final image. If there is a significant correspondence, the interaction is neutral, since there is not an important difference between the first and final image. Otherwise, the interaction can be positive or negative. To identify the type of interaction, the area of the blobs, that is present in the contours, between the two images has been considered.

3.1.2 Retail test

The tests were conducted in two phases. During the first phase the development of the procedure to verify the performances of the system has been realized thanks to the collaboration of Grottini Lab that provided the material and, moreover, allowed to test the system in their laboratory and successively in a real store, partner of Grottini Lab. The collaboration with the partner has been very useful to decide the arrangement of the system, according to functional strategic locations for sales and for the input monitoring.

All the system has been installed on a panel in the suspended ceiling of the store. Each system gives in output a significant amount of data that are stored in a database, so that they can be successively analyzed to extract indicators. The final test in the real store has been realized installing four RGB-D cameras for a time period of three months, in order to obtain significant and real data.

The cameras monitored the entrance, the bleach zone, the perfumes zone and the shampoo zone . The choice to put a camera near the entrance allowed to exactly count the number of people who entered the store. The indicators that are useful to evaluate the shopper behavior and that can help the store staff to understand their preferences and finally, to increase the sales, are:

- Total number of visitors;
- Total number of shoppers;
- Number of visitors in a particular zone;
- Number of visitors interacting with the shelf;
- Number of interactions for each person;
- Number of visitors becoming shoppers (sales conversion);
- Average visit time.

Some indicators that consider the interactions can be:

- Number of products picked up;
- Number of products relocated on the shelf;
- Number of products touched;
- Duration of interactions;
- Average interaction time;
- Number of interactions for product and for category.

(a) (b)

Figure 3.7: Details of Shopper Analytics roll out phase. (a) Camera installed above shelves of Ferrero's products. (b) Camera installed on Angelini's pharmacy showcases.

During the second phase has been realized a roll out of six months duration. The system has been installed above eleven shelves to analyze the interactions with the Ferrero's products and at the same time the camera has been also installed on four showcases of Angelini's pharmacy, figure 3.7.

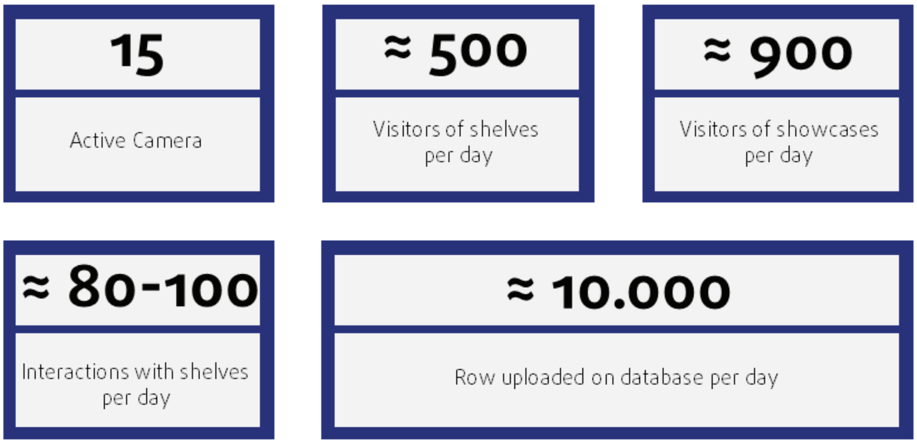


Figure 3.8: Statistics per day of data collected.

During the observation period the system have collected a lot of data. In figure 3.8 is possible see the daily statistics of data collected. During the 6 months of analysis have been added to the database an average of 10,000 rows per day. In front of the shopping windows of Angelini's stores in Milan and Rome Termini have been collected an average of 900 passages of which a 15% with a dwell time greater than 5 seconds and 25% with a dwell time between 3 to 5 seconds . From the cameras situated above the shelves, the analysis of data flows has showed a rate of data collection approximately 80-100 interactions per day per shelf and 500 average steps per day per shelf.

Regarding the cameras positioned on Ferrero's shelves to verify the reliability of the system the data collected has been compared with with sell index. As shown in figure 3.9 the number of interactions, even more consistently, follows the trend of sales in particular in the promotion period where the interactions confirm the increased attention that has been reserved for that selected product.

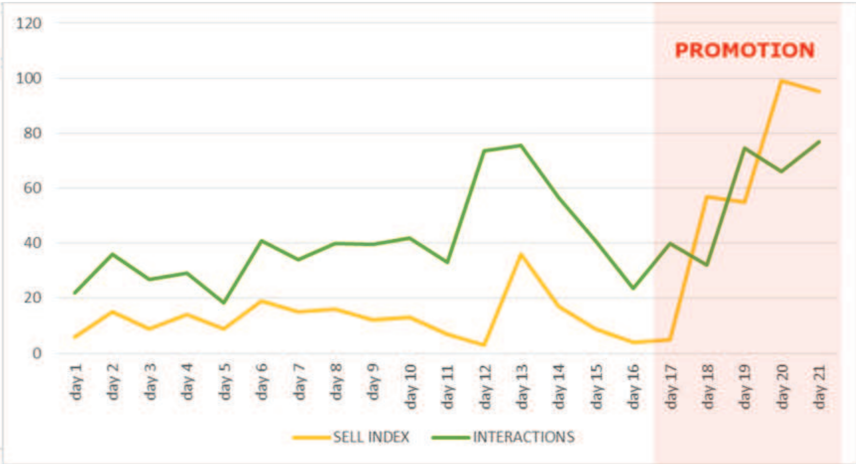


Figure 3.9: Interaction and sell intex trends of a selected product during test period.

3.2 Planogram Integrity

The Planogram Integrity solution here proposed is a system, mainly based on a smart camera, able to acquire and to analyse significant parameters of a retail store in order to detect differences from an accepted situation, i.e., an approved planogram. This is a complex task, so it is essential to propose an innovative solution that allows concentrating all the surveys and the necessary measures on a limited number of devices. Moreover, these devices must be of simple and immediate installation and in communication between them. The main idea is to easily and quickly install these smart cameras by using the lower possible amount of connecting cables and by building the camera as a modular structure. These features allow optimizing both the cost of the camera and time and costs for installing the system. The main three novel aspects are:

- The embedded sensor: the battery based camera is a new design very specialised for the purpose here described and it is a quite unique solution on the market with a really strong emphasis on power consumption; image processing procedures, data transmission and representation are totally focused on the general design of having a low cost, high scalable, high resolution, battery based smart vision system.
- The cloud based data infrastructure: retail industry is intrinsically distributed and scalable (store chains have hundreds of stores displaced all over the world with tens of shelves each); at our knowledge this is the first cloud-based system that considers the shelf and its planogram as a part of the IoT world in order to: extract data from a smart sensor, share it, inform end users and perform deep learning on collected data to train the

system to learn new information and to autonomously provide solutions to problems.

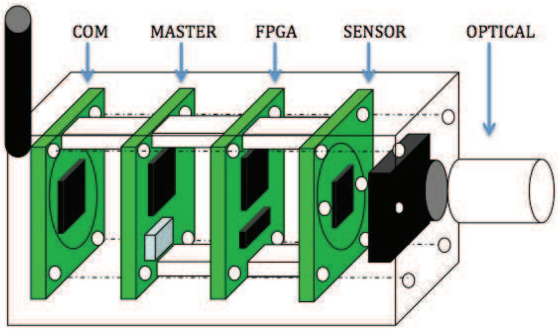
- The application: automatic planogram inspection is a really novel application in the scenario of IoT; it will ensure strong impact on the grocery and retail market by bringing to sell-out improvements and advancing store management state of the art. The proposed architecture automatically verifies the compliance of the planogram by simply taking a snapshot of the shelf. Then, the system provides information of incorrect displacements by means of a software GUI (see results section). A periodic intervention of the staff is necessary, usually at opening and/or closing time, since the project is not focused on automatic replenishment, rather on automatic detection using low cost, battery based sensors. Therefore, the adjective "automatic" mainly refers to the change detection approach, performed using only a minimum amount of apriori knowledge (the correct planogram or "first" snapshot). Besides, the system provides a fully automated measure of the correct product displacement in terms of percentage of planogram compliance.

The embedded system proposed integrates both the camera and the software for image processing and computation of differences all in a low cost architecture (of about 200 dollars). With respect to the state of the art, the system is battery based and very easy to install and use as a tool to provide a diagnostic measure over a finite time period (e.g., 2 weeks) and then to define a policy according with store staff. By collecting data from multiple shelves and from different stores receiving only synthetic data (i.e., percentage of planogram compliance), the cloud based architecture of the system is a crucial aspect to make planogram analysis in geographically distributed retail environments. At our knowledge, the proposed solution is the only affordable and scalable solution available on this field: it provides an easy to install, low cost, scalable and affordable solution to the problem of planogram maintenance, both from the hardware and software point of view. Moreover, the system gives, over an Internet of Things (IoT) cloud based architecture, a lot of additional data not concerning the planogram, e.g., out-of-shelf events promptly notified through SMS and/or mail, thus opening to future works and improvements of the system on the more general aspect of shelf knowledge and understanding.

3.2.1 System architecture and method

According to the main specifications, the aim is to realize a smart camera with the following characteristics:

- small size;



(a) Illustrative smart camera scheme.

(b) Two views of the real camera

Figure 3.10: The smart camera

- battery supply;
- low battery consumption (> 6 months of operations)
- high resolution images;
- ability to capture images in the infrared frequency (not essential for the purpose of this work);
- transmission via Wi-Fi of information acquired;
- interface to connect other additional sensors;
- modularity.

Figure 3.10 shows an illustrative scheme, figure 3.10a, which highlights the five different components, and two different views (figure 3.10b) of the smart camera.

Modularity is necessary to allow configuring the smart camera according to the real needs of each specific environment to be monitored. In this way we will be able to optimize the costs of the whole system.

Figure 3.11 makes explicit the communication among the smart camera modules. Components are strictly connected together. Modules are separated mainly for design and revision simplification. An important characteristic of

Figure 3.11: Diagram of the five components with their input/output connections.

NAME	DESCRIPTION & TECHNICAL SPECIFICATIONS
COM	Wi-Fi data transmission module.
MASTER	Master module managing the feeding of each module and the IIC interface for external devices, as well as connections to battery, to external power and to another smart camera to achieve stereoscopic vision.
FPGA	Image processing module (Field Programmable Gate Array, FPGA).
SENSOR	Management module of the optical sensor that acquires and processes images detected by the sensor.
OPTICAL	Optical module with focal lens.

Table 3.1: Description of each module of the smart camera

the proposed architecture is to be able to easily remove or upgrade a single module without the need of a complete redesign (i.e. a new vision sensor, a communication protocol different from Wi-Fi, a new FPGA and so on). Each of the five modules is described in detail in Table 3.2.1, considering also its technical specifications.

The smart camera described provides images to capture the physical location of products on the shelves. Figure 3.12 shows an example of a frontal image of product positioning. The system knows the planogram, i.e., the better position of the products on the shelves. So to detect planogram integrity, the system automatically matches the approved planogram, stocked in the server, and the pictures from stores. Departing from the image acquired from the acquisition module of the smart camera, the implemented system matches the planogram image (base) with the acquired image and provides a comparison image, calculating the differences between the two images. The algorithm compares the images detecting areas with "big" differences in dimension, by subtracting the corresponding pixel of each image and providing an alert when the difference is greater than a fixed threshold. The interest is not in change detection that involves areas smaller than the dimension of a single product, these "small" differences are considered as noise and deleted.

In Figure 3.13 the architecture of the implemented software is presented. As an example of the system we show how it acts when an image is acquired and matched with the accepted planogram. Observing figure 3.14, there are two

Figure 3.12: Example of planogram used in the retail market and described by an XML file. This format is typical of several planogram description software available in the market. The most famous is Spacemen, distributed by Nielsen.

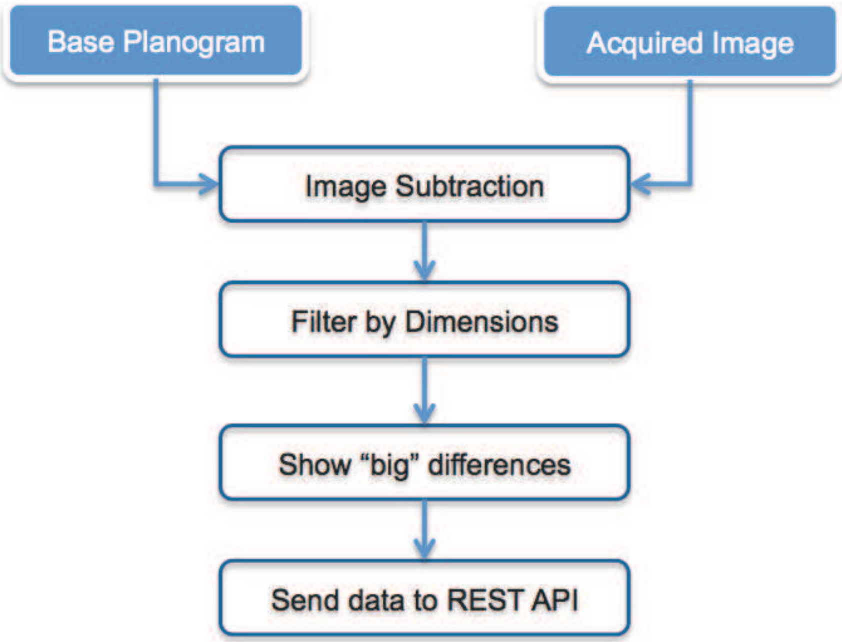


Figure 3.13: Representation of the implemented image processing algorithm.

images of example: image (a) represents the planogram, while image (b) is the acquired image, clearly referring to the same scene/shelf in different moments.

Analysing figure 3.13, the algorithm processes two input images: the image representing the accepted planogram (base planogram) and the image acquired by the smart camera at a later time. It has to establish how the actual image is different from the planogram accepted as correct. Image subtraction is the

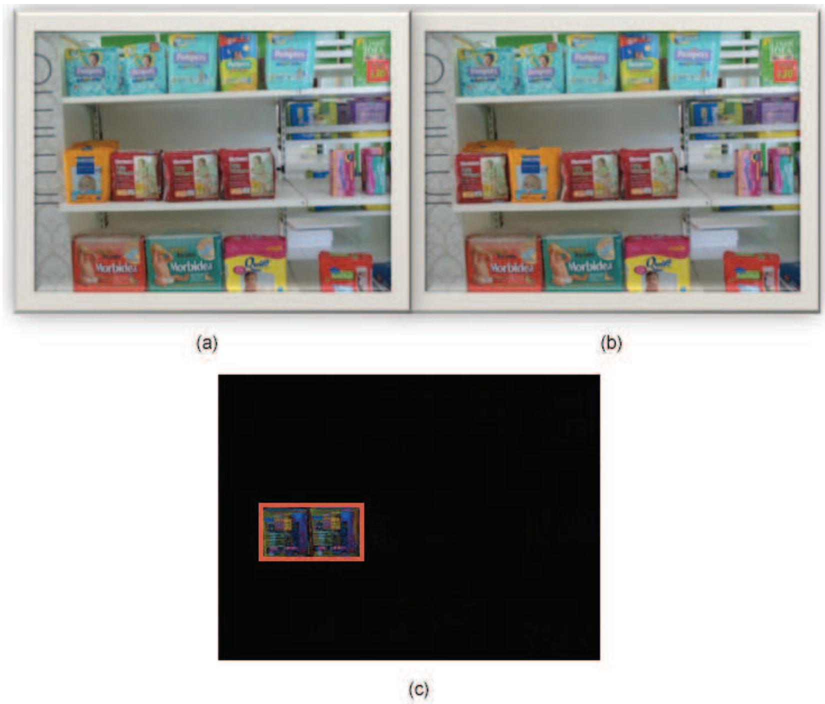


Figure 3.14: Comparing two planogram images: (a) planogram image (base planogram) (b) acquired image (actual image) (c) visualization of the difference image.

result of this comparison. Each pixel value of the first image is compared to its corresponding pixel value in the second image. If the difference between the two values exceeds the fixed threshold, the pixel is represented as color difference between the planogram pixel and the reference pixel, while if the difference is less than the threshold, the pixel in the difference image is black, as figure 3.14c shows.

Before saving the difference image, the output of the image subtraction module is processed by the Filter-by-dimensions module, which eliminates, that is puts to black, pixels associated to noise. Then the Show-"Big"-differences module represents the difference image. Observing the images in figure 3.14 we can see that, in the second image, the planogram has not been completely respected, since there are items in wrong positions.

The algorithm detects the problem and signals the differences by reporting the vertex coordinates of the bounding box of the detected area (showed in figure 3.14c by red lines). Only these geometric information are stored in the sensor-cloud infrastructure described in the next section and used for the statistic layer. A local threshold, implemented in the smart camera, is used to exclude small areas and can be manually configured according to the dimension of the smallest product on the shelf.

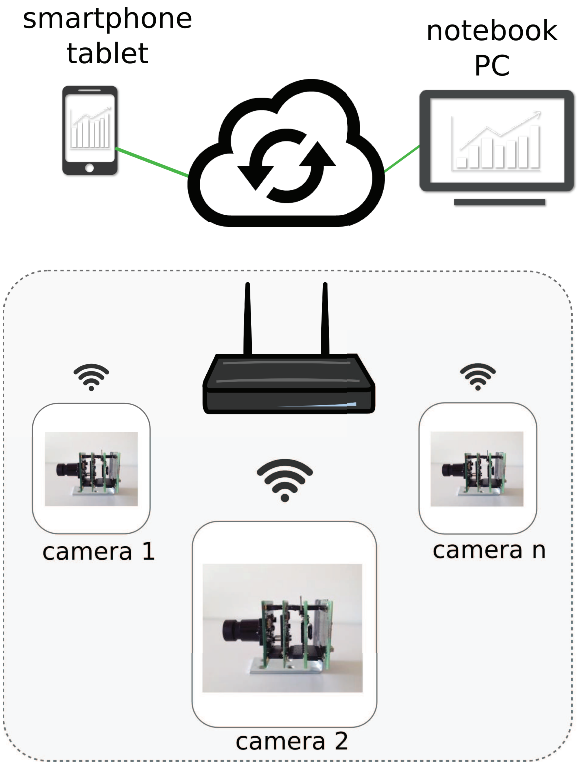


Figure 3.15: The Sensor Cloud Architecture.

The non-black pixels in figure 3.14c represent products that in the acquired image are not in a correct position with respect to the planogram image. As we said, this situation will be promptly notified through an alert. If the difference image is completely black, there is a situation of planogram integrity.

In a real configuration the arrangement of products in the shelf could not be so ordered as in figure 3.14. On the contrary, the recognition of multiple instances could be interfered with many reasons: bad illumination, bad positioning, rotation, translation and, in particular, objects partially occluded. Obviously, in these situations with many differences signalled, the system results less useful than in cases with only few differences, because it requires a robust, supervised intervention of the staff.

The web based architecture can be described as a Sensor-Cloud infrastructure.

Figure 3.15 shows a representation of the Sensor-Cloud infrastructure. Basically every camera is a sensor node that transmits synthetic raw textual data to the cloud over the Wi-Fi connection. So, each camera communicates with the cloud architecture by means of a Wi-Fi transmission data. Data can be processed through different devices (smartphone, tablet, or notebook).

In the proposed application every node (smart camera) is a sensor able to send synthetic data to the cloud. The cloud based web application allows to:

- define the region of interest (ROI) of the reference image sent by camera in the first configuration phase;

- define users at different levels to access statistics and to receive alert (via mail or SMS);
- store data from every node into a database to allow detailed analytic reports;
- define alert threshold as a maximum level of planogram errors;
- send alerts via mail or SMS when the alert level of planogram errors is reached;
- compare data coming from different categories / different stores.

All the software is provided as a service and is fully developed in Php language, using a MySQL DBMS. The reporting system is based on Spago BI. An example of analytic report interface is reported in the next section.

3.2.2 Description of experiments

In the experimental phase, the camera was fixed at 2 meters above the floor at a distance of 3.5m with respect to the centre of the shelf. The maximum visualization area was of 1.8m x 3.2m, wider than the height of the shelf (1.5m). This experimental set-up is showed in figure 3.16. The camera is in a fixed central position and in the experimental phase have not tested the performances of the system by rotating or translating the camera.

Tests were performed in two real stores in Italy both in the diaper shelves. The computational time to elaborate differences between 1280x960 images is of about 760 msec.

We measured the power consumption of each board in idle state (Pidle) and at full load (Pmax), i.e., with the radio transmitting, the camera acquisition and the algorithm running. For the shelf monitoring application here described, it is reasonable to assume that, with a monitoring period of one minute every day, the smart camera powered by 2 C batteries (Long-Life Alkaline, Size C, 1.5 Volts, 7000 mAh), will last for about one year. Indeed, the camera and the algorithm can run just once a day, usually just before the store opening time, therefore the board will be on for less than 2 minutes every day (considering a frame rate of 1 frame per day, the start-up time, the elaboration time and the data transmission via Wi-Fi).

Table 3.2 reports different consumption tests to prove the efficiency of the actual choice. The duration of the battery results inversely proportional to the resolution of the image. We took into account only image resolution for two main reasons: i) time parameters are not very important because our system

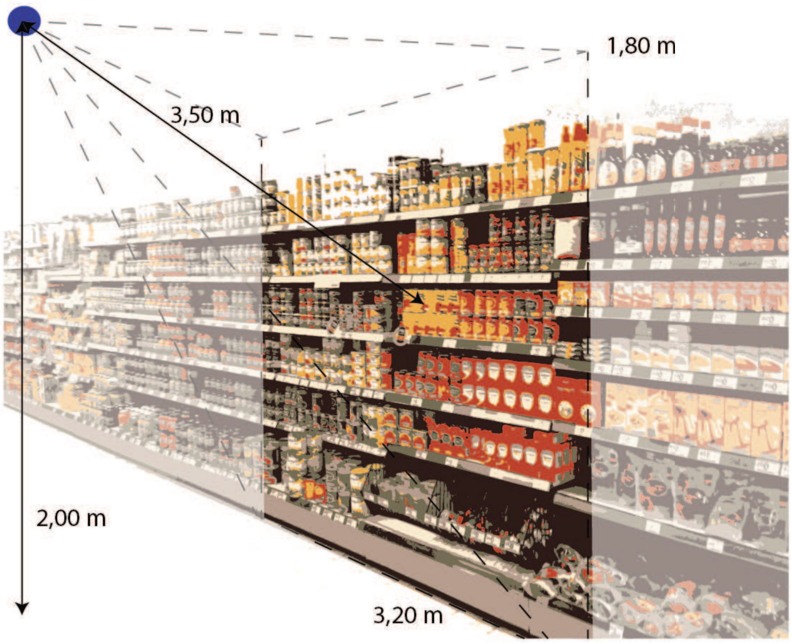


Figure 3.16: Representation of the experimental set-up.

takes only one snapshot of the shelf a day; ii) the performance of the system in verifying the integrity of the planogram strongly depends on the resolution (higher is the resolution more precise is the comparison between base planogram and acquired image).

Solution	Resolution	Time (days)
Actual solution	1280x960	360
High Resolution	2560x1920	60
Low Resolution	800x600	900

Table 3.2: Battery based life time vs image resolution

Real data have been essential to test the overall behaviour of the system with regard to different lighting conditions (even if the store is an indoor environment the external light causes deep increase of light during day or night), occlusions (people passing by), store people behaviours (refill team working on the area, wrong products positioning). The system installed run for 25 days collecting a huge amount of data and different events on planogram maintenance. In particular the total amount of pictures processed were about 1000. In this period planogram errors have been also monitored manually, day-by-day, to have a ground truth able to evaluate results of the automated process. Incorrect product displacements have been measured by evaluating manually the differences between day-by-day measurements. Comparing the manual annotations with the results of the system we reached a 96% of reliability with

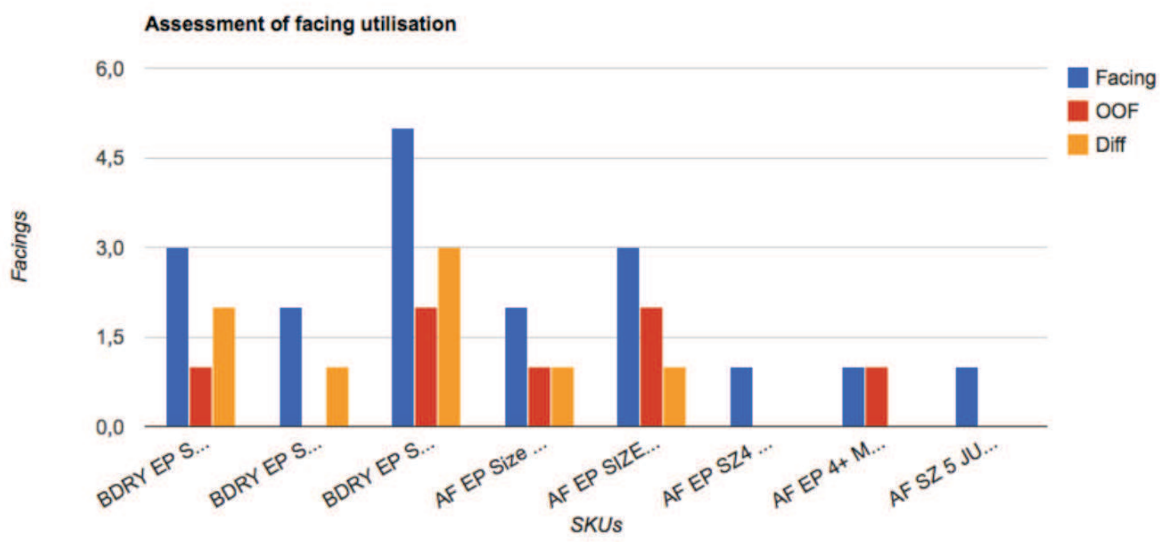


Figure 3.17: Comparison between the base planogram and current Out Of Facing (OOF) of products for different Stocking Keeping Units (SKUs) in the shelf. Differences (Diff) can be useful for planogram optimization based on optimal space allocation.

respect to ground truth.

The system provides reports showing a comparison between the planogram and the real usage of the products in the shelf. This provides several new ideas on the way to improve the planogram profitability for a typology of store that sales a specific category of products: motor vehicles, electronic equipment, chemicals, toys, household products (detergents, diapers, cosmetics), and so on.

In the experimental phase, we consider a specific store of diapers as dataset, as figure 3.17 shows. The yellow bars in figure 3.17 highlights the presence or not of a pack of diaper (characterized by a brand, a size, colours, and so on) in the shelf, by comparing the base planogram with the image acquired by the camera. This comparison is useful not only to detect differences from the base planogram, but also to prevent eventually shelf-out-of-shelf. The product is not in the correct position because may have been moved respect to the position of the base planogram, or may be finished (shelf-out-of-stock problem).

In figure 3.17 blue bars show the number of facings on the current planogram, red bars show the real number of facing utilisations based on real-time data coming from Shelf Detector sensors [47]. Yellow bars are the differences between the previous two and, basically, suggest which kind of implementation should be applied not only for the planogram integrity but also to improve the planogram. Every camera send its data to the cloud server using the REST API provided by the proposed data architecture. Every message contains the total compliance percentage ($total_{err}$) measured as the ratio between wrong placements and total measured area, in pixels. Several bounding boxes indicated by x_1,x_2,y_1,y_2 and an identification value also describe every wrong placement area. Every camera is linked to the store and is also described by a configuration file that gives to the system information about geometry of the camera installation, IP of the gateway, and so on. Follow have been proposed an example of a JSON Schema.

Listing 3.1: Example of a JSON Schema.


```
{"store": {
        "id": "1"
        },
        "camera": {
                "id": "99",
                "total_err": [{
                        "perc": "12",
                        "time": "2012-04-23T18:25:43.511Z"
                }],
                "areas": [{
                        "ida": "1",
                        "x_1": "11",
                        "x_2": "29",
                        "y_1": "141",
                        "y_2": "173",
                },
                {
                        "ida": "2",
                        "x_1": "123",
                        "x_2": "229",
                        "y_1": "1041",
                        "y_2": "1096",
                }]
        }
}
```


Using the proposed data architecture the brands, retailers and visual merchandisers can extract comparative data between categories or stores, can use data to link them to other source and obtain useful insights, can apply premiums or penalties to store that have great or bad planogram maintenance performances.

3.3 Smart floor

As already described in the state of art, the research activity in recent years has seen the development of many types of smart floor. Below have been proposed an implementation with the aim of enabling the replicability of the system, reduce production and installation costs and maximize performance in terms of localization of objects and people in space to study the human behavior as retail environments and in particular danger situations such as falls. The work of analysis and tests of the smart floor has been developed in collaboration with several companies and Andrea Gatto professor of University of Modena and Reggio Emilia.

3.3.1 System architecture and method

The localization and tracking of users in a specific space has in recent years become a goal of computer science researchers. With the advent of smart environments, transparent user localization has become an even more pressing purpose than before the rise of these paradigms.

If a system could transparently follow the movement of the user, it could customize its interface and behaviour to match the references, history, and context of that particular ambient so as to intervene in the case of necessity or danger. Easy installation, long life and reliability of the whole system are other fundamental aspects of this solution.

There is a large number of recently works that focused on more passive forms of user localization in enclosed spaces, such as people recognition and tracking using video, noise analysis using audio systems, distance analysis using optical or ultrasound sensor [61]. One of the most interesting way to localize people in an enclosed space is based on pressure sensing systems integrated into the tile or wood floors.

To better way to serve this function, the smart floor should have the following features. It must have a low cost of installation and operation, it must be invisible, easy to install and implementable on existing structures, it should quickly and accurately identify the location of user. Indeed the reduction of the waiting time after a fall is a priority goal. Therefore it is prevalent the need for immediacy of local processing of the signal by transmitting only the result. The minimum frequency of sampling for efficient processing of data is 7 Hz, the distance of the positioning of sensors on the floor (or mesh grid) is 180 mm. Moreover, the maximum limit for recovery of energy is 5.8 J by step otherwise the walking on sand problem will occur. For these reasons, the designed solution uses capacitive sensors on polymeric support to be inserted between solid wood and wooden part of a floating floor, as shown in figure 3.18. These capacitive sensors are connected with the driver board placed between

Figure 3.18: Capacitive sensors on polymeric support installed between solid wood and wooden part of a floating floor.

the tiles of floating floor, as shows in figure 3.19.

The system is also able to detect a falling using a simple multiple sensor activation.

For practical use of the system, have been proposed a new approach to customize the system instead of training an activity model for new users. In the modelling phase, have been build a pool of activity models from a group of people. Localization and fall data are classified for human behaviour analysis purposes by an activity model, composed of Bayesian networks and support vector machines constructed through the processes of pre-processing and model training. The pre-processing module filters out noise, segments the data every half second, and extracts statistical features (minimum, maximum, average, median, standard deviation) from the smart floor data. On the contrary of conventional approaches, which construct a population model or train an individual model for a new user, have been applied a best matching activity model in the pool of activity models already constructed from the other people.

The system thus created does not need to power the control unit, except for the task of collecting data from the various sensors and process all the information. The main critical aspect is represented by the capacitive measurement, which is very sensitive as phase is changing. The cable is usually insulated with Teflon to address this problem.

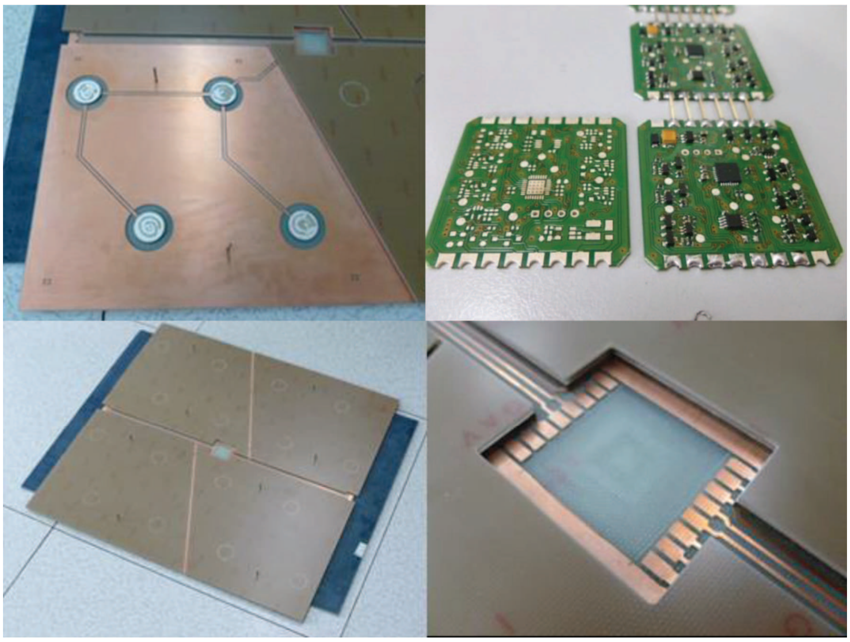


Figure 3.19: Capacitive sensors and driver board connected and placed inside the tiles of floating floor.

The data from the various sensors are arranged in a matrix, used to describe and discretize the area being monitored, and stored on a server cloud. This information will be analyzed to implement features of tracking in space. The matrix is the description of the state of the system and is contains the pressure information coming from the sensors. In case of significant variations, or with a predetermined time interval, this matrix is sent by the processing and control unit to the server that has the task of processing the raw data read by the sensors. The analysis algorithm implemented on the server uses this information on the distribution of the surface pressure not only for the localization of people present in the area of interest, but also for the detection of particular situations, such as the fall to the ground of a person. If the increase of the distribution of surface pressure in a contiguous area becomes greater than the surface pressure of a standing person and is consistent with that of a person lying on the ground then we can deduce that the person is not located in standing but is lying on the floor in a potentially dangerous situation.

The smart floor implemented has been tested in collaboration with the University of Modena and Reggio Emilia to measure in detail the performance of the floor with appropriate test equipment. Other test have been done in Grottini Lab showroom to validate the indoor localization.

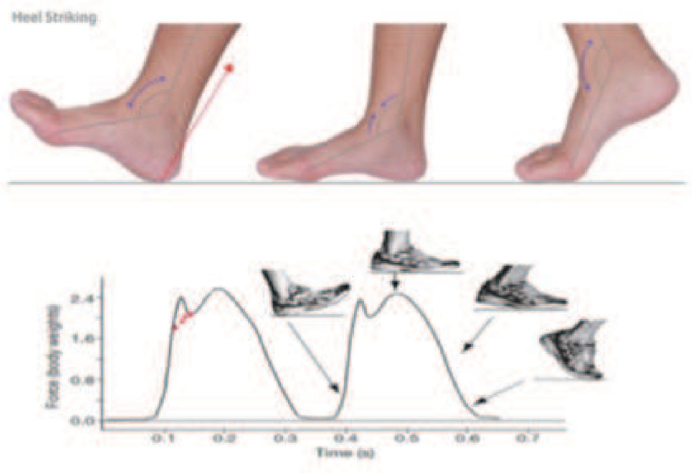


Figure 3.20: On the top, the movement of the foot. On the bottom, the forces exerted by different states of support.

3.3.2 Description of experiments

The simulation test of the floor functional prototype must reproduce the following different phases: heel strike-contact phase; midfoot strike, stance phase; forefoot strike, or flaking; the initial one can last up to 60% of the entire cycle, this can be achieved by varying the height of the springs of the recliner plan. Figure 3.20 shows different phases of the step. The top of the figure represents the foot highlighting the curvature angle. The bottom of the figure puts in evidence the correlations between the forces exerted by the body weight and the instants of the step. Rejected the hypothesis consisted of letting a person walk back and forth for days, we have assumed an original test.

The prototype designed for the testing phase on the floor is showed in figure 6 the design choices introduced are: the contact angle between the plane of the school and the ground is about 20 and the contact force has an initial peak increasing from a normal deambulation (stance phase 60% of cycle time) to the running (stance phase 40% of cycle time). A medium person usually runs 120 steps per minute, the period per cycle is 1 second, while at a speed of 20 km/h the cycle time drops to 0.6s, the contact phase changes from 0.62 to 0.2 s. The contact force increases until it reaches multiple of body weight with increasing speed of the race. So the simulation test must be conducted with a load equal to approximately the body weight (sinusoidal load equal to +30% body weight) and with a frequency from 30 to 120 (maximum) steps per minute (0.5-2 Hz). It was decided to operate with sinusoidal load, with frequency 1 Hz avoiding the original peak since shoe's proposals are suitable for normal walking and not for running. The shoe was mounted on a form with a joint that allows a rotation between the front and rear of the foot (further details can be found

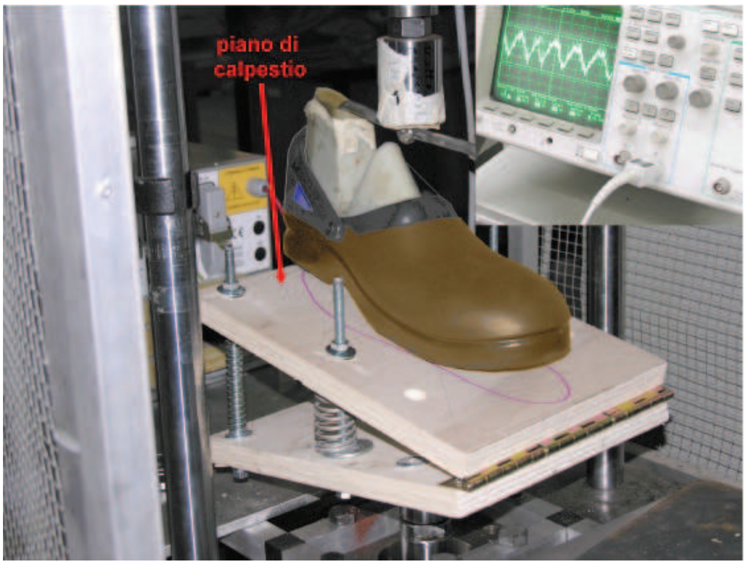


Figure 3.21: Prototype for the testing on the floor.

in [11]). The novel result of this paper if the long life test performed with the system depicted in figure 3.21 The tile has exceeded 1,000,000 cycles (test conducted with a load of 0-600 N at a frequency of 2 Hz) whit the voltage measured in open-circuit decreased by 16%. Given that a tile of side 0.3m is placed in a room of 16 square meters, the smart floor has a probability of being trampled of 0.5% ; even assuming to be on a preferential path attended 20 times more than the average, the value of 1,000,000 cycles can reasonably equate to an infinite life time. In order to check the effectiveness of the solution a lots of simulations of use were performed. The guidelines adopted for this simulations are: check that the possibility of not intercepting a sensor in two steps was negligible or very limited and verify that, moving from any point, the possibility of intercepting a sensor is characterized by an isotropic distribution.

Figure 3.22 shows the positions of the foot as a function of the first step and the step mode: distance perpendicular to the advancement of the footprint, distance in the longitudinal direction of the impression. Figure 9 also indicates the possible effect of the change in direction of the pass. Simulations allow to conclude that, although it is theoretically possible that a single impression can be placed without intercepting any sensor, the chances of this happening again without changing the direction of the axis of the foot with every step, is negligible.

Figure 3.22: Long life test scenario.

3.4 Indoor trolley tracking

The UWB solutions for indoor tracking of people and objects are the most efficient in terms of accuracy, reliability and autonomy. For this reason it was chosen such a system to implement the tracking of trolleys and baskets in stores and large exhibition areas. After a short description of the technology and the tracking algorithm used will be compared two hardware solutions currently available on the market that use the same radio module. Finally, will be illustrated the tests performed in the Grottini Lab showroom and in a real store.

3.4.1 System architecture and method

The goal is to develop and test a system based on UWB technology, able to monitor the path of customers in stores and send the tracking data collected to a cloud server. These data, properly processed and stored in a database can be used to obtain useful information about customer's behaviour. UWB technology theoretically allows to get an accuracy of 10cm in terms of indoor localization and along with a smart power management provides a high autonomy for the tags, that are battery-powered. The coming to the market of UWB radio module DWM1000 (IEEE802.15.4-2011 UWB compliant) by decaWAVE,

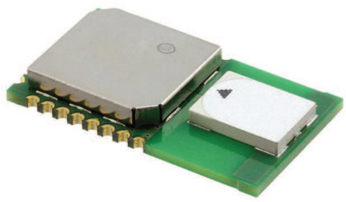


Figure 3.23: DWM1000 decaWave module.

figure 3.23, at a low price (10 dollari per 1000 unit) has given rise to a great number of tracking solutions, developed by European companies, not always at low price.

This solution can be easily integrated in a retail environment. Placing UWB antennas properly in the area to be monitored and tags on shopping carts and trolleys it is possible to know in real time the location of most of the customers shopping at any time in the store. Reconstructing the covered paths, average walking time and stop time it is possible to derive useful information and indexes that now are estimated only using few measures like people counting at gates, sell out and audit. These data tell us just a little about how the customer interact with the environment, which areas are the most visited, if he has difficulties in finding what he needs and what are the most effective strategies in terms of marketing, communication and space design. In order to collect and process these data the system illustrated in figure 3.24 has been developed. Two different demonstration UWB kit has been evaluated in terms of performance: Sewio and OpenController.

In order to analyse the UWB performance we used two demonstration kits provided by different companies: Sewio and Openrtls. Sewio provides a kit composed of 4 anchor, 1 master, 4 battery-powered tags and a Raspberry to elaborate 3D data for the tracking, figure 3.25. Openrtls provides a kit composed of 4 anchors, 2 battery-powered tags ad a master responsible to calculate the position. Both use Time Difference Of Arrival (TDOA) algorithm in order to calculate tag position within the range covered by the anchors. Prior to install the system in the store, in order to acquire data regarding customer's behaviours and routes, a test has been conducted in the Grottini Lab showroom. The test environment has been described in figure 3.26.

Both systems implement a real-time location system and to perform the tag's localization within the area covered by the antennas the TDOA algorithm is used. Multilateration is based on arrival time difference (TDOA) of a signal emitted by a tag to anchors placed in an area. The key concept of TDOA based

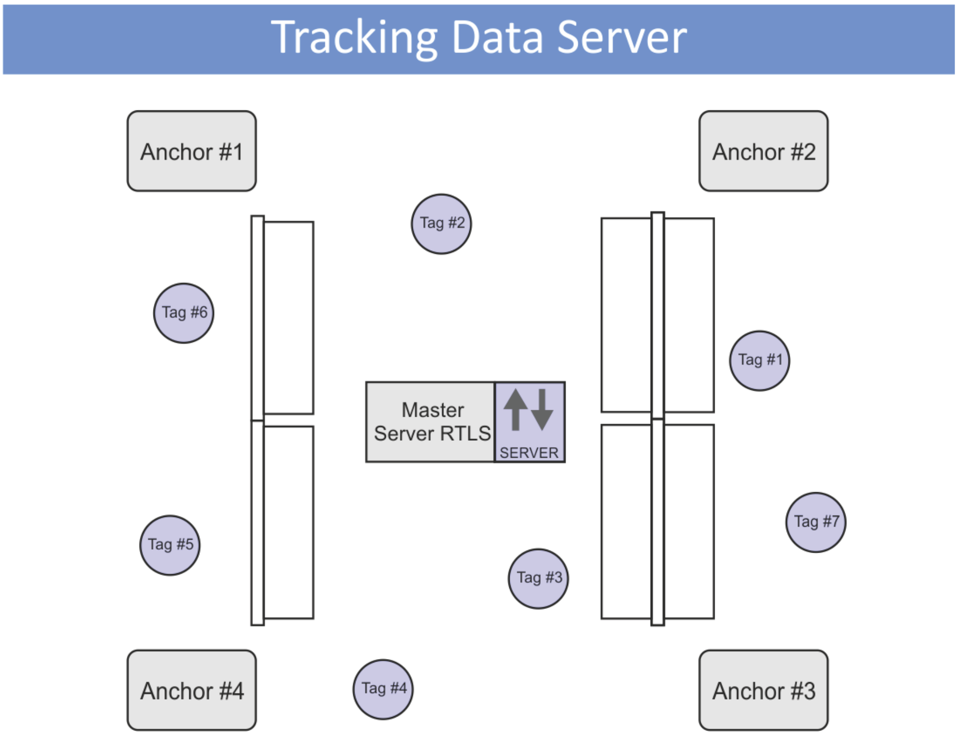


Figure 3.24: System architecture.

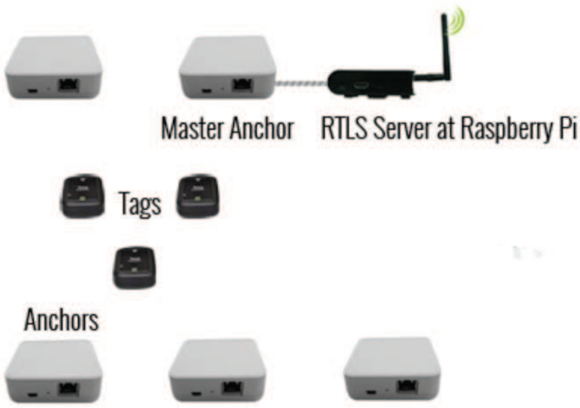


Figure 3.25: Sewio UWB kit.

localization technique is to determine the location of the source by evaluating the difference in arrival time of the signal at spatially separated base stations. To calculate the time difference, the synchronization among the base stations is additionally required by using a synchronization process in practice. After an initial set-up phase in which is necessary to fix the position of each antenna and the master, it is decided what type of filtering to apply to the measure and

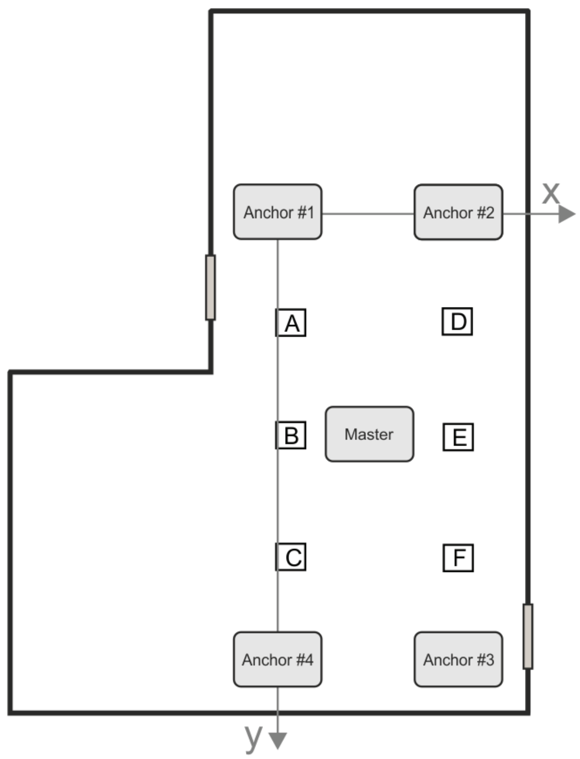


Figure 3.26: Showroom test.

whether to make an average on the last three measurements, it is possible to start localization.

In order to evaluate the performances of the kits, we placed the anchors in the same positions and later compared the measures indicated by the systems. In the figure 3.26 we can see the positions of anchors in the showroom. In table 3.3 there is a comparison of localization 2D measures in six known points for the two kits. As we can see, looking at the measured data in the showroom, the kits provide same results in terms of reliability and accuracy.

The average error is about 15cm. The main difference in a real scenario of a retail environment is represented by batteries lasting time. The tags in Sewio's kit implement energy saving features crucial for a greater tag autonomy, which are not present in Openrtls's tag. Only the tags of the Sewio's kit implement features and power saving options to achieve greater autonomy. After 10 seconds of inactivity, indeed, these tags are put on standby and through the use of inertial sensors such as the accelerometer, is possible wake up the system and resume localization once the tag is moved back again. These features allow to increase the autonomy bringing it from few days to several months.

Both UWB systems send tracking data collected from each tag on TCP/IP socket in unicast, multicast or broadcast mode. For this reason a software has been developed responsible to collect from the stream some informations

Table 3.3: Showroom test

		Measured	Sewio kit	Openrtls
Point A	x	80	77	85
	y	188	195	192
Point B	x	80	87	82
	y	457	443	450
Point C	x	80	85	87
	y	646	637	640
Point D	x	412	430	418
	y	191	200	199
Point E	x	412	423	420
	y	459	441	447
Point F	x	412	395	417
	y	655	641	648

such as the ID of the master, the tag ID, the coordinates (x, y and z) and battery level from each tag and timing informations such as timestamp of the tracking system and computer where the software is running. The data are first structured within a JSON structure and then sent to compounds packets from at least ten localization measures, via POST method to the server. The JSON structure used to send and collect data to a cloud server responsible to store them, in order to simplify their access to a later analysis.

```
{"masterID":XXXXXXXXXXXXXX,
    "numTAGS":"XX",
    "tags":[
    {
        "tagID":"XXXXXXXX",
        "x":"XX.XX",
        "y":"XX.XX",
        "z":"XX.XX",
        "timestamp1":"XXXXXX",
        "timestamp2":"XXXXXX",
        "batterylevel":"XXXXXX",
    },
    {
        "tagID":"XXXXXXXX",
        "x":"XX.XX",
        "y":"XX.XX",
        "z":"XX.XX",
        "timestamp1":"XXXXXX",
        "timestamp2":"XXXXXX",
```

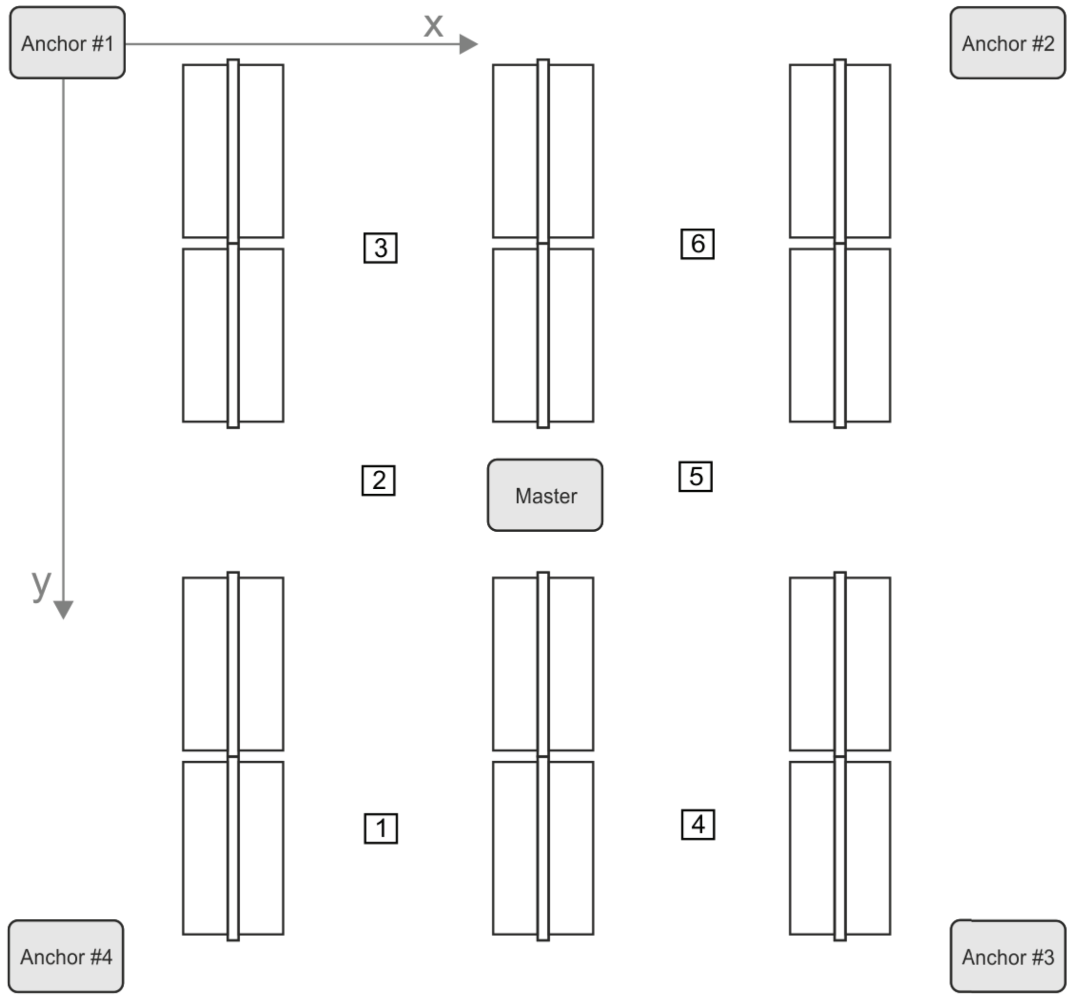


Figure 3.27: Retail test

```
        "batterylevel":"XXXXXX",
    },
    ...]
}
```

3.4.2 Retail test

After having verified the best performance in terms of battery life for the Sewio kit's tag it was decided to only use this system for the testing inside the "SiConTe" store. The system has been positioned, as shown in figure 3.27, so as to cover an area of 10m x 10m in beverages and soft drinks sector. For simplicity, the anchors and master were placed on mini tripod and powered by the 5V batteries 10.000mAh which allowed easily to realize the tests in the entire of a store opening day schedule.

In figure 3.28 is possible to note the enclosure developed and 3D printed for the integration of the tag on the cart used during the tests.

Figure 3.28: 3D printed enclosure

		Measured	Sewio kit
Point 1	x	345	300
	y	642	615
Point 2	x	345	329
	y	358	349
Point 3	x	345	313
	y	33	11
Point 4	x	677	724
	y	642	587
Point 5	x	677	619
	y	257	203
Point 6	x	677	708
	y	50	13

Table 3.4: Retail test mesaurement (cm)

In table 3.4.2 some of the 2D-data collected have been presented. As it can be seen in the real environment the location 2D system presents a different behaviour from that shown in the showroom. The error on measurement increases and probably due to the presence of the shelves in metal and various obstacles is not uniform on the space.

Even varying the data filtering options provided by the Sewio localization software are not seeing a significant improvement in the localization measuring. In figure 3.27 also presented a heat map extracted from the analysis of data collected during the day.

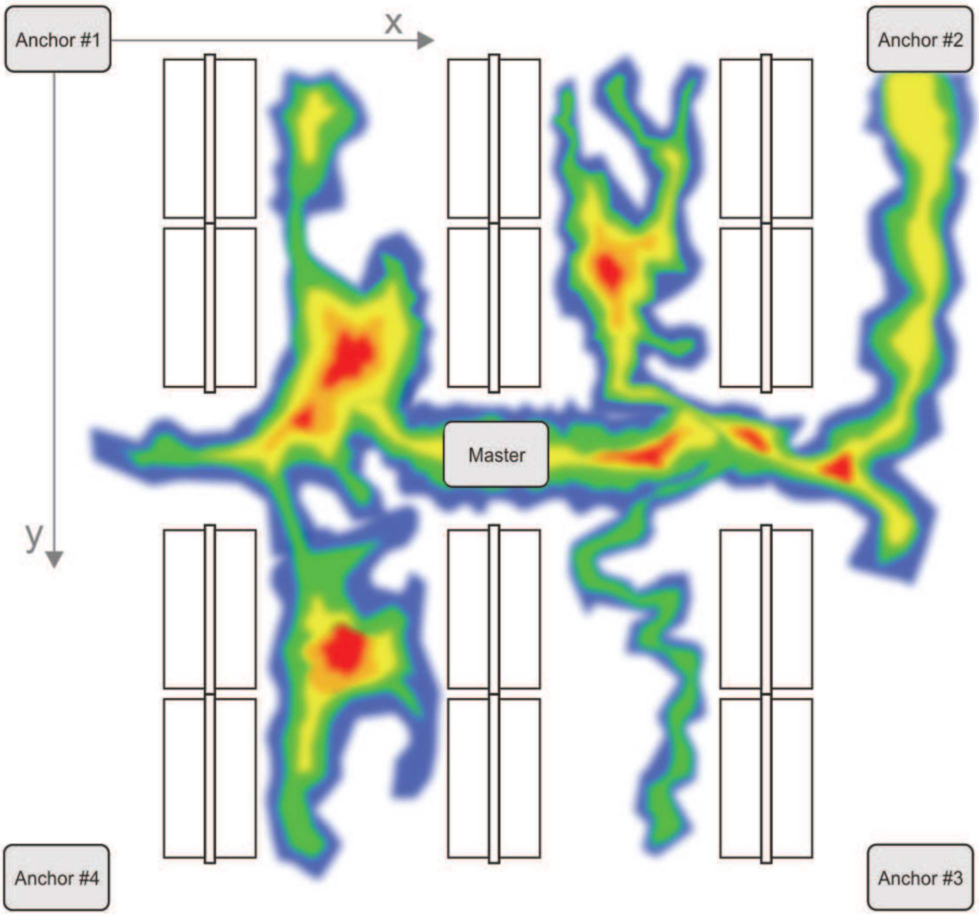


Figure 3.29: Heat map realized with the data collected during SiConTe test.

Chapter 4

Shopper conversion: a real application

The previously presented systems are today still under test and intensive development. The aim is that to continuously improve performance and reliability. However two of these technologies, Shopper Analytics and the indoor trolley tracking system are already very interesting for several customers and in collaboration with GFK company has been carried out a pilot in a real store.

The installation has been made at June 2016 in a german store, figure 4.1. The pilot project is named Shopper Conversion. The aim of this installation is to test and validate an in-store customer behavior measurement system able to follow the movements of trolleys and baskets and thus the customers via the UWB system and at the same time able to analyze the interactions of customers with the shelves of the categories chosen to perform the analysis.

More generally, the designed system consists of a group technologies named micro that includes all technological solutions able to measure in detail the customer behavior in specific points of interest with the use of RGBD camera and another group called macro that includes all technological solutions that allow to obtain a general idea about customer behavior in the retail spaces.

Figure 4.1: A detail of the german store.

In the following sections will be presented in detail the system integration activities done to install and connect the solutions. A dashboard developed to read and analyze the data collected by the two systems with the heat map and key performance indicators will also introduced.

4.1 About the architecture

The german store has a size of about 1500 square meters. The goal of this project is to measure the store performance with the use of Shopper Analytics and the UWB indoor trackin system provided by Sewio. Data are processed according to figure 4.2, described below, with the following functionalities:

1. Sensors inside the store gather data from the real environment using the two technologies described before (RGBD / Micro, RTLS / Macro).

2. Every category and sensor have an in-store single processing unit (embedded mini-pc) that manage: data processing, communication layer to send data to the cloud using a WiFi/3G connection, communication failures with local data cue, maintenance signals and alarms, tag battery management.

3. Raw data are collected on a AWS service in real time (with available connection) or following a recovery procedure of the data cue (during night time). Data cleaning is done directly at raw data layer.

4. Middle layer is responsible for data aggregations and give as output different Data View described below.

5. Data Visualization Layer is implemented based on a AWS Cloud Middle layer using a mix of Tableau dashboards and custom heat-map visualizations.

4.1.1 Macro system technology

In order to adequately track the UWB tags movement attached to the carts, 20 anchors have been placed inside the countertop, wired via LAN cables and powered with PoE solution, figure 4.3.

Tracking data can be correlated (by X,Y location and timestamp) with those from other customer behaviour monitoring technologies such as webcams, sales and so on, making a complete and detailed measurement tool to analyse customer behaviour in stores and evaluate the performances of the store. Actually Macro data are collected by moving carts once every second.

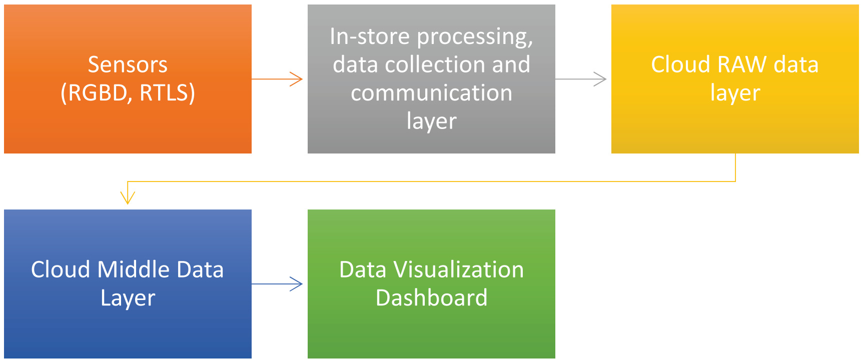


Figure 4.2: Data collection and processing schema.

Figure 4.3: A detail of an anchor placed inside the countertop.

Location data are collected and processed by a computer server, this also installed on ceiling, that deals to manage and send data to Amazon AWS platform. Amazon Kinesis service handles the streaming flow and with the use of the features offered by another tool called Firehose, deals to storage the data on Amazon S3 cloud as logs and send the same data to Redshift, a non-relational database also hosted on Amazon server. The figure 4.4 visually summarizes this process.

The data once collected are processed daily by a Java script for the calculation of routes, dwell time and number of unique visitors. The script uses the Java framework map and reduce Implemented in Hadoop activated in Amazon. This approch allow to scale the performance and improve the performance. To derive the number of visitors since the tags are installed on trolleys and not on the customers it was established that we can define a new customer every time the tag resumes to transmit after an idle time of 15 minutes. All these elaborations allow to obtain a lot of information and generate heat map to understand quickly what are the most visited areas and what are the routes made.

Figure 4.4: Data workflow implemented with Amazon AWS services.

Figure 4.5: An example of RGB-D camera installation on ceiling.

4.1.2 Micro system technology

During the first phase GFK has required to analyze the interactions with RGB-D camera on the shelves belonging to three categories: dairy, oils and spirits, figure 4.6. Therefore have been installed respectively 6 camera for dairy, 3 for oil and 5 for spirits category. In figure 4.5 an example of RGB-D camera installation on ceiling. An additional camera has been placed at the entrance to only monitor the number of visitors, and then the inputs and outputs from the store. As shown in figure 4.7 each camera has connected via USB cable to a mini PC where runs Shopper Analytics software and is interconnected in a LAN network to a 3G router to send data on AWS Amazon cloud.

Micro technology has the main purpose to measure some relevant index , as for i.e. :

- most attractive area of the shelf, a real vertical heat map shows how the shoppers interact with the products available on the shelf. Thanks to this information it will be possibile to measure the impact of new products, new offers, new promotion, new packaging and so on.

Figure 4.6: A detail of spirits category.

Figure 4.7: Configuration hardware of Shopper Analytics mounted on ceiling.

- most inteacting SKUs, interactions are divided in three different types :
  - Positive, shoppers touch the product and "buy" it;
  - Negative , shoppers touch the products , hold for a while and return it to the shelf;
  - Neutral , shopper just touch the products without holding it.

  These informations are extremely useful to understand the real interaction between shoppers and products.

Also these can be used to understand how the shoppers flow on the :

- traffic flow in front of the shelf , measure the real traffic of the shoppers in front of the shelf:
  - passing by;
  - stop;
  - avg time spent in front of the shelf.

These informations can be useful to identify the "proximity" traffic of the shelf.

In this context to effectively analyze all this great amount of data is crucial define KPIs and design a dashboard that can group the data and make the information collected easily accessible. In the next section we will illustrate the data collecting methods developed in partnership with GFK.

4.2 Dashboard and KPI

In order to understand the big data collected and quickly obtain the store's performances have been defined seven key performance indicators (KPI): total store visitors, customers present in category, customers stopping in category, customers interacting (touch, hold), customers purchasing, purchase ratio and average interaction per visitor.

A dashboard has been designed with the Tableau tool to analyze properly the data collected. Tableau is a business intelligence software that allow to realize easily graphs, tables and widget to export data.

All the data easy collected in this web based dashboard and safely stock in a cloud space are extremely useful to understand shopper's behaviour and create new, tailor made and more powerful marketing approch, also to better manage the store team in term of people employment based on the most busy period of the day, refill strategy, associates turnover and last but not least, better area to provide communications as offer, special deal etc. , particularly :

- What is the impact of shelf marketing material? How to test shelf claims, shelf talkers, other shelf material, POS material, etc.?

- What is the optimal shelf assortment and/or shelf planogram? How to measure shelf re-design?
- What is the optimal secondary placement? How to measure the impact of secondary placements?
- What is the current closure rate and conversion? How to improve the different stages of conversion?
- What are the drivers for spontaneous buying behavior? What changes the initial shopping plan?

All data layers are on HTTPS and with a login (onelogin on SAML 2.0) integrated with AWS and Tableau. Users can be defined and associated to a group. Every group can have user rights for every single page of the dashboard.

Following a list of definitions to better understand the following metrics and to define a common terminology.

- Cockpits – The home page of the dashboard with an overall view of all principal metrics.
- Store Visits – The page of the dashboard with people and carts entering the store metrics.
- Store Heatmap – A daily aggregation of people passing by a grid cell heat map and dwell time per cell.
- Category Funnel – A page in the dashboard with funnel conversions (entering, passing, stopping) and interactions conversions (touch, bring back, buy).
- Store Visitors – Number of different people entering the store (returning visitors are counted twice).
- Dwell Time – Time each visitor spend in the store (Time difference between store exiting timestamp and store entering timestamp).
- Walking distance – Total geometric distance a visitor steps inside the store from the main entrance to the exit area.
- People – Customers counted and tracked by the RGBD camera (Micro).
- Carts – Customers holding a cart counted and tracked by RTLS tags (Macro).
- Group – People entering alone (single), together with someone (couples), or in a group with more than 2 people (families).

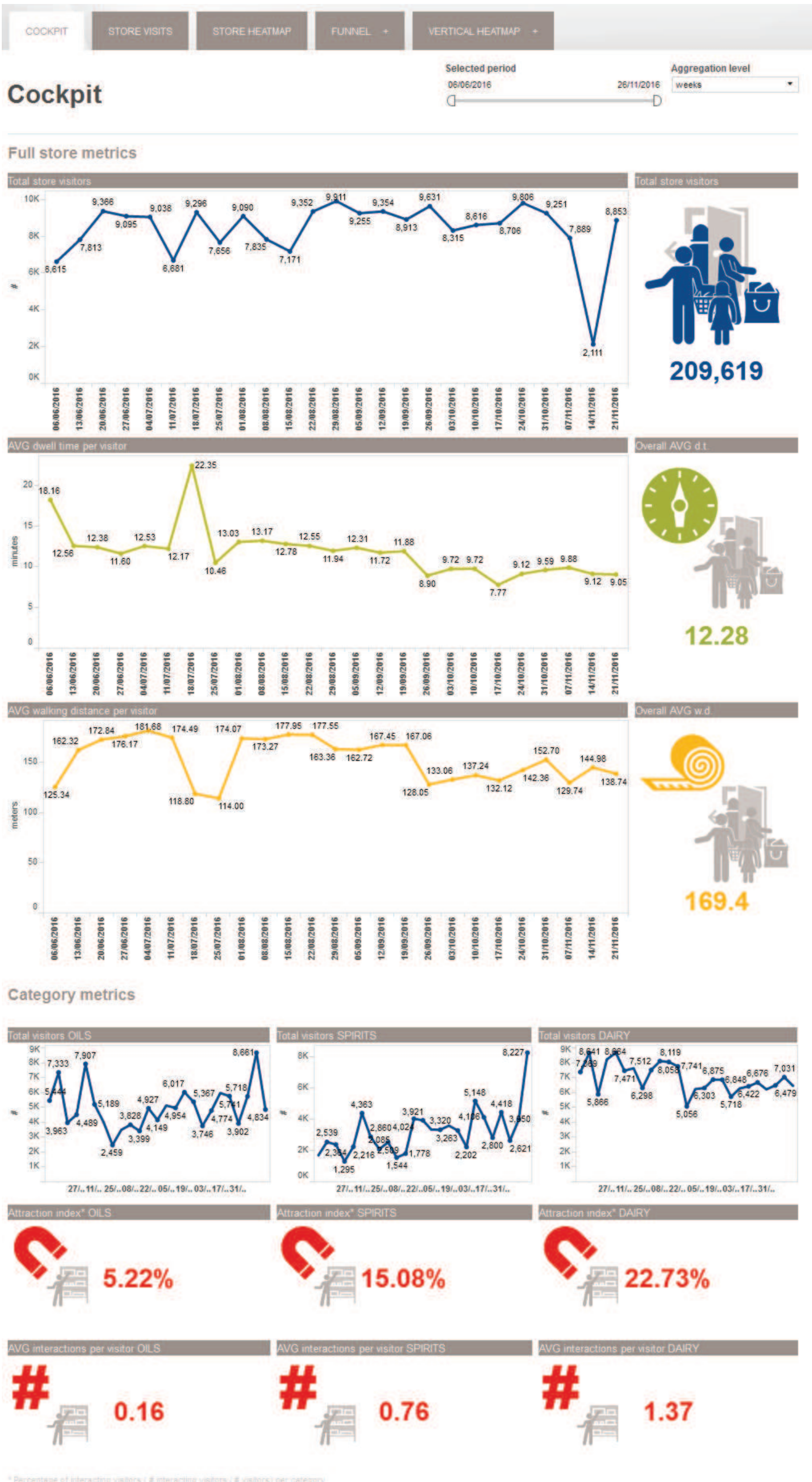


Figure 4.8: The dashboard implemented to analyze data.

As shown in figure 4.8 the dashboard developed have five sections.

- The first section is named Cockpit and summarize the most interesting information about the performance of the store, figure 4.9. Inside this section there are the full store metrics as number of visitor, dwell time per visitor and average walking distance per visitor, all metrics are reffered to a specific period. In addition there are the information about the category metrics in terms of two KPI: attraction index and average interactions per visitor.

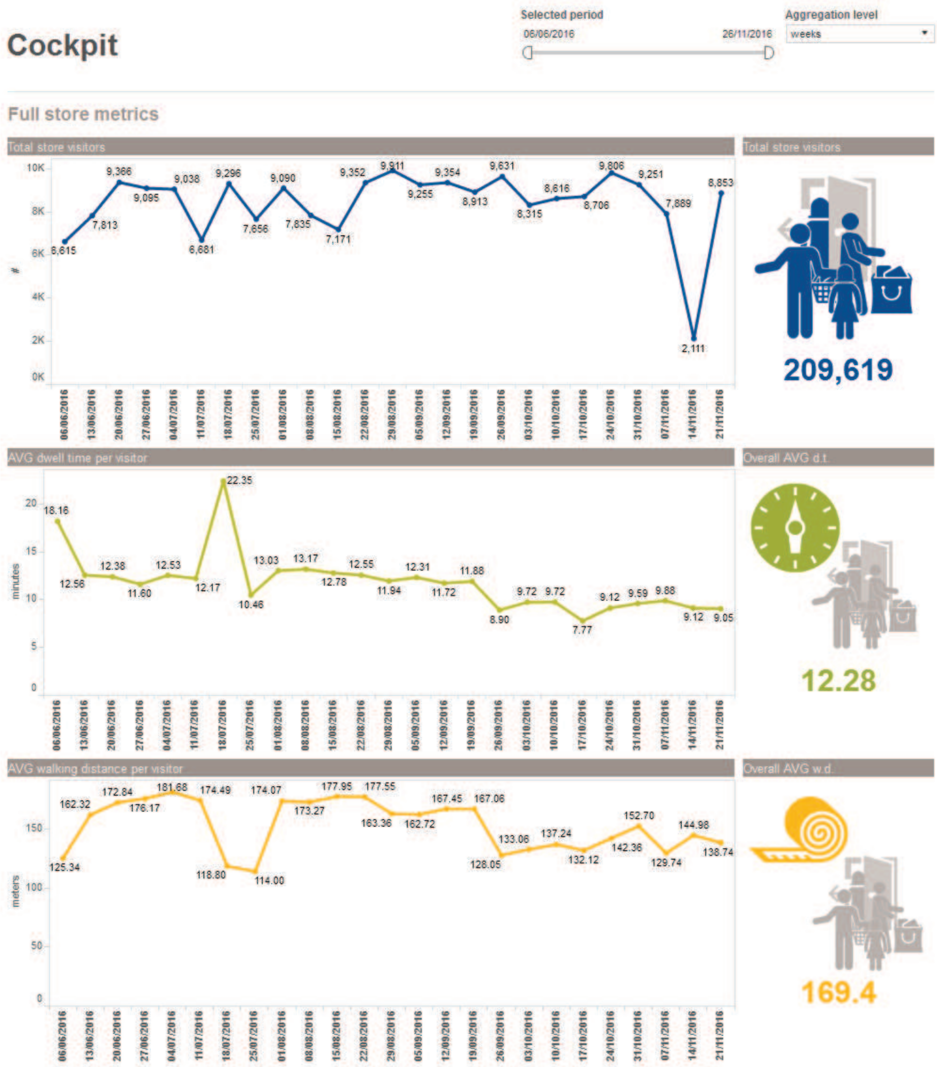


Figure 4.9: Dashboard: cockpit section.

- Another section is named Store Visits and shows the data about the number of visitors, number of carts used and group metrics to know if the people entered are single, couples or families, figure 4.10.

- The other section presents the heat map of store, figure 4.12. In this

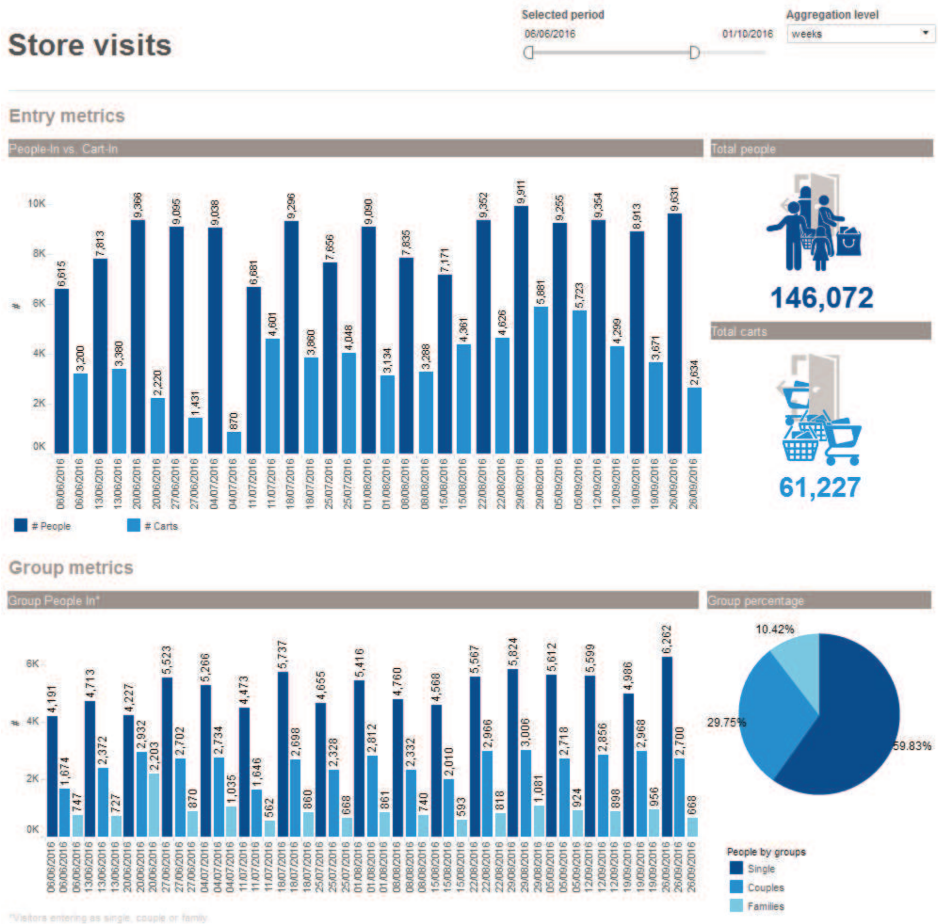


Figure 4.10: Dashboard: store visits section.

page is possibile to analyze the most visited areas, the main routes and the distribution of the dwell time in store. The dictionary meaning of heat map is the graphical representation of any individual value. The matrix of this representation is represented by colors. The different colors that are seen in this graphical representation have different meaning or depict different values for different data. However, in Retail the heat map help the Retailers in many ways like, knowing the hot spots, dead areas, bottlenecks and in performing A/B tests The store heat map system takes data coming from trolleys and carts and helps the Retailers to have an idea about the customer's traffic pattern in a particular time window. Heat maps are collected processing on a daily base data coming from RTLS data, gathered from the store at a frequency of 2Hz for every cart and basket moving around. The grid map is represented by cells with a physical dimension of 50 cm by 50cm, covering all the store area. This dimension is related to the average localization error that is about 30cm with respect to the real cart position in the store. Every single cell is described as a Geometry ID i and collects data related to number of carts or baskets passing and average dwell time per carts and baskets, figure 4.11.

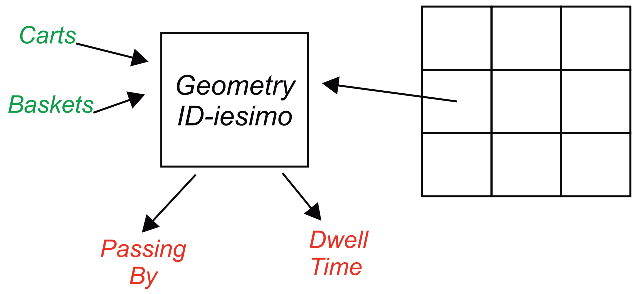


Figure 4.11: Single cell aggregation data of heat map.

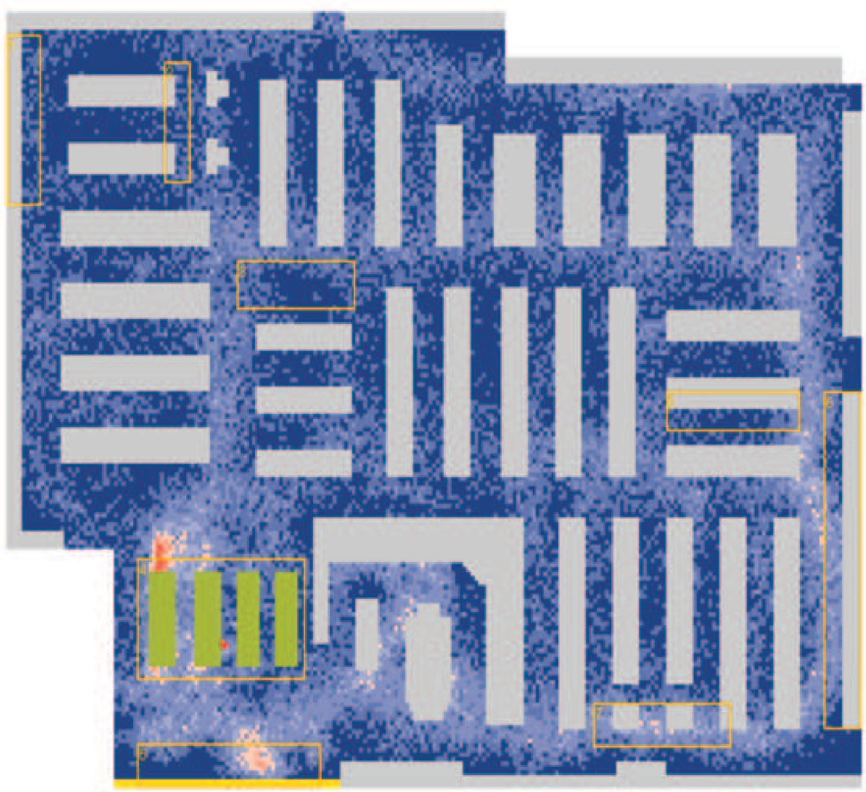


Figure 4.12: Dashboard: heat map section.

- The section Funnel allow to make a zoom on each category. Inside this page, figure 4.13 is possible to study the performance of category selected in terms of number of visitors per category, number of stops in category for a period greater than 5 seconds, number of interacting visitors, number of purchasers and several convertion ratio as: interaction/stop, average interactions per visitor, conversion ratio purchased/interaction and average purchases per interactor.

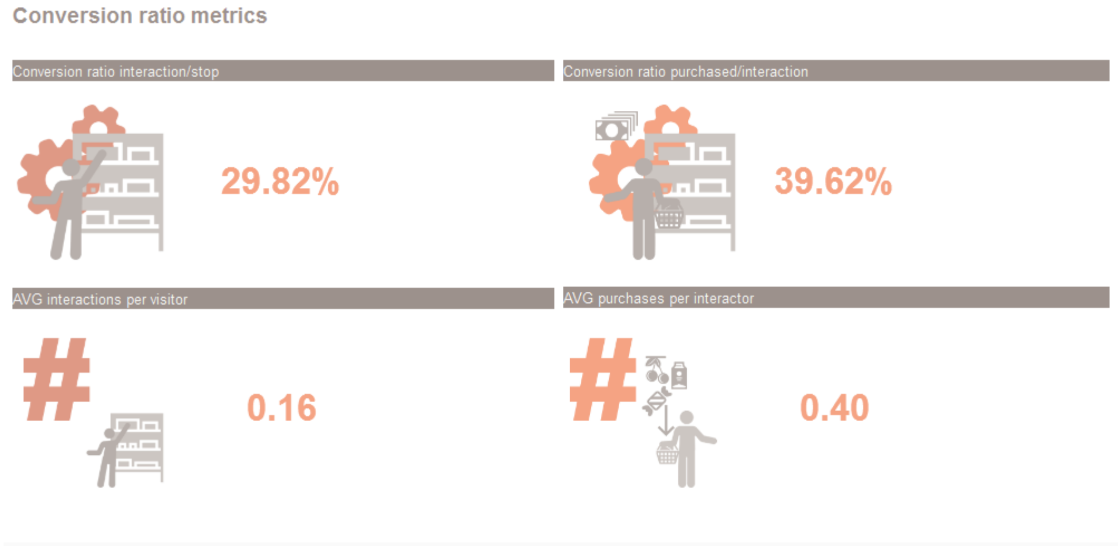


Figure 4.13: Dashboard: funnel section.

- The last section named Vertical Heatmap shows the spatial distribution of interactions on the shelves of each category 4.14.

Figure 4.14: Dashboard: vertical heat map section.

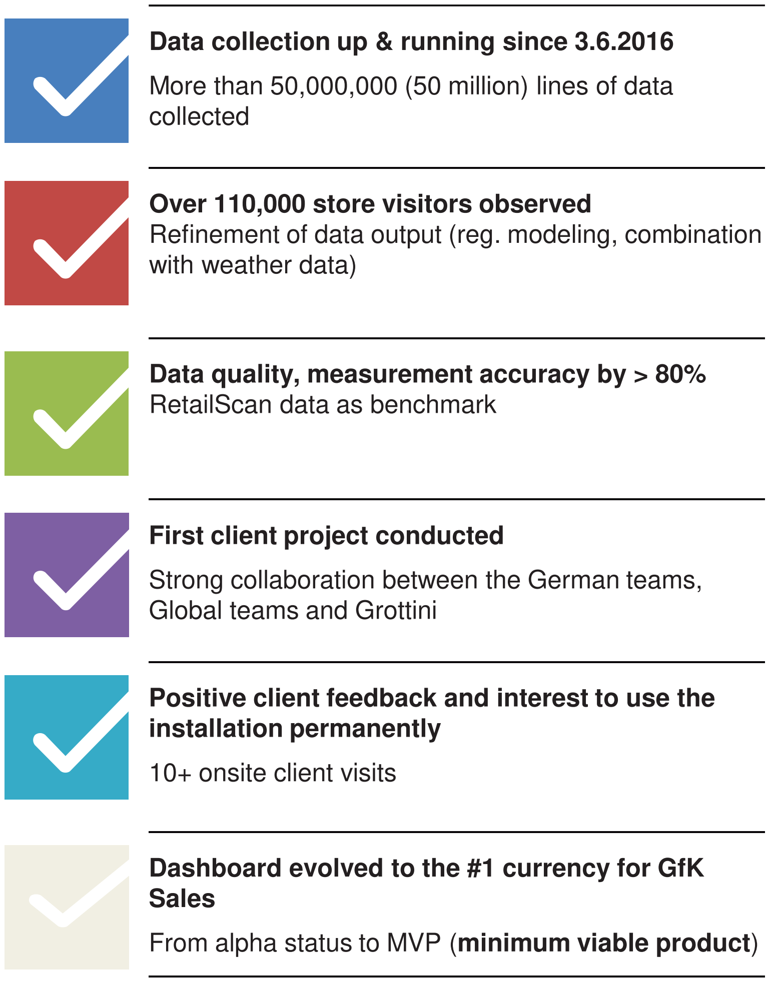


Figure 4.15: Pilot results after six months observation.

The pilot activated by June 2016 in about 6 months has collected about 50 million of row data uploaded to the database with a measurement accuracy about 80%, 4.15. The results have proven the efficiency of the technological solutions installed in order to evaluate the store performance and to study in detail the customer behavior in particular during commercial offer periods or after planogram changes, category shifts and store redesign.

Chapter 5

Conclusion

In this thesis three different technological solutions have been presented useful for the analysis of customer behavior in stores.

Shopper analytics: software that thanks to the use of an RGB-D camera allows to study the customer behavior near the shelves, analyze the type of interaction, dwell time and the number of visitors.

Planogram integrity: an IoT smart camera able to analyze the planogram maintenance and the location of products on shelf.

Smart floor: an intelligent floor for the localization of people and objects in space using self-powered capacitive sensors.

Indoor trolleys tracking: a UWB system for indoor tracking that makes use of powered tags to track the path of trolleys and therefore the movement of customers in stores.

All data collected through the use of IoT protocols are sent to a cloud server, stored and processed for analysis and study of informations. Have been presented also KPI and data aggregation methods.

Several tests have been performed, in particular for Shopper Analytics and the indoor trolleys tracking system. After an initial roll out phase, has been implemented a second phase of testing on a real store. This last phase has has had a duration of six months, has allowed to collect 50 million of data with a measurement accuracy around 80% and has analyzed the behavior of 110.000 store visitors.

The results collected during the test periods in real stores have allowed to retrieve a lot of information about customer behavior. The implemented solutions are able to provide the necessary information to retailers and brands respectively to optimize spaces, planograms and also to improve products and marketing strategies.

The positive impressions gathered by the partners with whom Grottini Lab collaborates to install the previously presented solutions confirm the goodness of the research undertaken that will certainly have several developments in the future. In particular concerning the management and processing of data through a careful analysis of information collected according to the needs of retailers and brands.

In addition to the processing and data optimization, other possible developments that can be done relate to the improvement of the Shopper Analytics system by replacing the RGBD sensor with the latest high-performance time-of-flight (TOF) sensors and implementing new features such as the people re-identification in multi-camera monitoring systems. About the tracking indoor the main aspect regards optimization of performance and accuracy of tracking indoor UWB systems and the integration with returned information from static tracking systems such as smart floor.

The necessity to collect data will be increasingly important and decisive in the future and this will allow to open new research scenarios on the one hand for the development of ever more efficient measurement solutions and on the other hand for the processing and interpretation of data collected.

In summary, main contributions and results presented in this work are:

- RGBD not invasive technological solutions useful to acquire the customer behavior in front of the shelf;
- innovative IoT solutions able to study the planogram integrity and implement an indoor tracking system using the UWB technology;
- a smart floor implementation able to locate persons and objects in retail environments;
- the techniques to collect, process and present data and results in terms of meaningful key performance indicators and dashboards.

Future works and main improvements can be done:

- in Shopper Analytics solution: replacing the RGBD sensor with the latest high-performance time-of-flight (TOF) sensors and implementing new features such as the people re-identification in order to recognize the customer and analyze the behavior of unique visitors only;
- improving the recognition and classification performances of the planogram integrity together with increased battery life;
- testing different floor materials and improving the measurement accuracy;
- analyzing new methods to elaborate and classify paths, movements and dwell time;
- improving dashboard, KPI and data optimization.

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