Coastal Monitoring System based on Social Internet of Things Platform

Published Version:
Coastal Monitoring System based on Social Internet of Things Platform / Roberto Girau; Matteo Anedda; Mauro Fadda; Massimo Farina; Alessandro Floris; Mariella Sole; Daniele giusto. - In: IEEE INTERNET OF THINGS JOURNAL. - ISSN 2327-4662. - ELETTRONICO. - 7:2(2020), pp. 1260-1272. [10.1109/JIOT.2019.2954202]

Availability:
This version is available at: https://hdl.handle.net/11585/800401 since: 2021-02-17

Published:
DOI: http://doi.org/10.1109/JIOT.2019.2954202

Funding Agency:
Italian Ministry of University and Research, within the Smart Cities Framework; 2018 IEEE International Conference on Internet of Things (iThings); IEEE International Conference on Green Computing and Communications (GreenCom); IEEE International Conference on Cyber, Physical and Social Computing (CPSCom); IEEE International Conference on Smart Data (SmartData), Halifax, NS, Canada, 30 July-August 3, 2018

Coastal Monitoring System Based on Social Internet of Things Platform

Roberto Girau, Matteo Anedda, Mauro Fadda, Massimo Farina, Alessandro Floris, Mariella Sole, and Daniele Giusto

Abstract—Coast erosion is a process that degrades a coastal profile and is mainly due to natural factors (e.g., related to climate change) and overcrowding (e.g., urbanization and massive tourism). While the first cause can be considered as a slow process, the growing presence of humans is leading to rapid aging of coasts. The Mediterranean Sea authorities are focusing on the necessity for a systematic and comprehensive approach to the management of littoral areas. In this context, Italy is searching for a promising solution to safeguard coasts but, at the same time, to manage in an intelligent and "green" way the big amount of tourists. Research communities all over the world indicated the Internet of Things (IoT) as a valid technology to develop solutions in order to try solving or mitigating the coastal erosion problem. IoT-based techniques allow to manage heterogeneous and massive data for real-time monitoring and decision making and can be used for coastal environment and crowd level monitoring. This article presents a monitoring system based on the Social IoT (SIoT), a new paradigm that defines a network where every node is an object capable of establishing the social relationships with other things in an autonomous way according to specific rules. Thanks to social relationships, all involved devices in the monitoring system (i.e., sensors, cameras, and smartphones) are able to collect and exchange information. The proposed system, developed and installed in Cagliari (Italy), is able to evaluate the occupational state of a beach considering environmental and crowding data collected by devices and feedback sent by users.

Index Terms—Cloud platform, crowd detection, eco-tourism, environment monitoring, sensor networks, Social Internet of Things (SIoT).

This work was supported in part by the Italian Ministry of University and Research, within the Smart Cities Framework (Project: Cagliari2020, ID: PON04a200381, and Project Netergit, ID: PON04a200490). This work was presented in part at the 2018 IEEE International Conference on Internet of Things (iThings), in part at the IEEE International Conference on Green Computing and Communications (GreenCom), in part at the IEEE International Conference on Cyber, Physical and Social Computing (CPSCom), and in part at the IEEE International Conference on Smart Data (SmartData), Halifax, NS, Canada, 30 July- August 3, 2018. *(Corresponding author: Mauro Fadda.)*

The authors are with the Department of Electrical and Electronic Engineering, University of Cagliari, UdR CNIT of Cagliari, 09123 Cagliari, Italy
(e-mail: roberto.girau@unica.it ; matteo.anedda@unica.it ; mauro.fadda@unica.it ; massimo.farina@unica.it ; alessandro.floris84@unica.it ; mariella.sole@unica.it ; ddgiusto@unica.it).

I. INTRODUCTION

Coast erosion is the process of wearing away material from a coastal profile due to an imbalance in the supply and export of material from a certain section. Climate change can be considered as one of the main reasons. The relative rise of sea level is the most important change as it implies an increase in sediment demand which, if not supplied, results in coastal retreat. Current predicted changes in sea level estimate a rise of up to 0.6 m by 2100 [1]. Higher sea levels allow waves to break nearer to the coast and transmit more wave energy to the shoreline. This phenomenon promotes erosion and coastal retreat at sediment starved locations. Sealevel rise is therefore likely to cause an inland migration of beaches and the loss of up to 20% of coastal wetlands [2]. While the erosion of coasts and beaches due to natural factors may be a slow process, the presence of humans can be a cause of alarm. Urbanization and commercial activities along the coasts or in proximity of the coastal zones are the main reasons for large-scale erosion and dwindling of the beaches and coasts. In recent years, mass tourism has also had a strong complex relationship with coastal erosion [3]. As a consequence, a growing amount of sand is taken away by beachgoers, both accidentally and voluntarily.

Considering the Mediterranean Sea, both local and national authorities recognize the importance of the coastal erosion problem and its implications for tourism, as well as the necessity for a systematic and comprehensive approaches to the management of littoral areas. In 1974, the United Nations Environment Programme (UNEP) established its Regional Seas Program (RSP) with the scope of coordinating activities aimed at the protection of the marine environment through a regional approach. The mediterranean action plan (MAP) was the first UNEP initiative developed under the RSP and became the model for other seas across the globe [4].

In 1975, the Mediterranean States and the European Community approved the MAP as the institutional framework for cooperation in addressing common challenges of marine environ- mental degradation. The mid-term strategy (MTS) has been conceived to protect both the sea environment and the coasts of the Mediterranean and to allow eco-friendly initiatives for the 2016–2021 period.

Also, Italy is interested to find a solution suitable both to limit the erosion of coasts and to manage the big amount of hosted tourists. With its 1840 km of coast, against the 5616 km of the rest of Italy, Sardinia includes sea and coastal environments of high naturalistic value, recognized through the establishment of protected natural areas. In this article, we illustrate a system architecture that allows cooperative monitoring of Sardinian beaches, in order to save the environment and to increase the quality of experience (QoE) for bathers.

Internet of Things (IoT) devices and applications can help solve or mitigate the erosion problem, also considering that cloud big data analytics and learning systems are playing an important role to provide intelligent new services [5]. In literature, several works showed how the use of IoT-based techniques allows to manage heterogeneous and massive data for real-time monitoring and decision making in different sectors and environments, as for example industrial process management [6], air pollution monitoring [7], or security [8]. Many IoT systems were also proposed in the last years for coastal environment and crowd level monitoring, which are shortly presented and compared in Section II. However, none of these previous works exploit the combined use of both environment and crowd level information to prevent or mitigate the erosion problem.

Furthermore, IoT involves an evolution also from a legal point of view, because the objects, identifiable and localizable, raise issues relating to the processing of personal data and to the protection of the persons to whom the information refers. From the objects, it is possible to go back to the people and, in particular, to their position. It is a real tracking of individuals: that object goes beyond a sensor that detects it and, therefore, knows that the object (i.e., a person) is in a certain place. If, for example, a sensor detects the presence of a person's cell phone (i.e., already possible when the Bluetooth is on and the cell phone is "visible"), it is possible to know the precise time its owner was present in that particular place; later, using other sensors, it might be possible to know that the same person got on the bus, then headed for the supermarket, and so on. In this article, a brief discussion on the rules taken into account to protect the privacy of peoples and to preserve collected data from malicious use is also discussed.

To address the above-mentioned issues, this article presents a system that leverages the Social IoT (SIoT) paradigm [9], according to which objects are capable of establishing social relationships in an autonomous way [10]. Thanks to the resulting social network, sensors, cameras, smartphones, and other devices located in the beach area can discover, exchange, and collect information to assess beach overcrowding. The idea is to involve people in the conscious choice of the beach to reach, both to limit the overcrowding and to improve the QoE for the bathers. The contributions of this article are as follows.

1) We define how the SIoT social network can be used to find the objects that can contribute to populating the training set of the crowd level classifier and can collaborate in the exchange of information about the wave height, water temperature, and other relevant monitored values related to the beaches.

2) Through demonstrating how this system runs in the Lysis framework applying the SIoT model, we present a description of the implementation. In particular, we propose a new element in the platform to distribute the trained classifier model to the ground stations on the beaches.

3) We propose a new algorithm to evaluate the occupational state of a beach considering the collected data. The system exploits users' feedback to help in creating training sets needed by the crowd level classifier.

Moreover, the proposed system acquires local data, such as temperature, wind direction, and ultraviolet (UV) intensity.

4) We illustrate some experiments of a real system deployment on several Sardinian beaches.

This article is structured as follows. In Section II, an overview of previous beach monitoring and crowd detection methods is presented. The cloud SIoT architecture is illustrated in Section III while the proposed monitoring system is described in Section IV, where also a short discussion on the privacy management of data is presented. Implementation details of the prototype are provided in Section V, whereas the experimental setup to evaluate the performance of the carried out prototype and the obtained results are discussed in Section VI. Finally, the conclusions are drawn in Section VII.

II. BACKGROUND

The coastal environment monitoring and crowd detection are two topics that allowed the production of lots of research articles in the last years. In this section, a short overview of methods and solutions is presented. Then, a comparison between the proposed system and the previous solutions is proposed in terms of key aspects identified during the analysis.

A. Beach Monitoring

There are several approaches in literature proposing the coastal environment monitoring systems. Bruno *et al.* [11] combined different software engines to fully exploit the COSMO-SkyMed images using the geological and remote sensing data, related materials collection in the research area, and historical statistical information to construct the environment quality evaluation index system in the nature reserve of Panjin red beach. In [12], several indexes were extracted using the image processing to evaluate the stress for an ecosystem, extracting data about shorelines. The main disadvantage of this proposed system is the incapability to reach detailed information about environmental parameters. A strategic measurement setup to monitor coastal erosion presenting a case study at a micro-tidal sandy beach located in Tamil Nadu has been discussed in [13]. Near-shore sediment regime, shoreface, and surf zone hydrodynamics were considered. Papakonstantinou *et al.* [14], deal with a method to obtain coastline processing high-resolution orthophotos derived by unmanned aerial vehicles (UAV). The photogrammetric UAV-based remote sensing approach reveals high-resolution digital surface models of coast. The methodology integrates UAV data, GIS, remote sensing, and 3-D visualization. To evaluate it, authors performed measurements in Eressos beach, Greece. Pikelj *et al.* [15] proposed a coastal erosion monitoring system based on low-cost structure-from-motion (SfM) photogrammetric imaging and multiview stereo (MVS) to obtain 3-D models of coasts in order to individuate changes in their morphology.

Shoreline position and subaerial beach volume are derived from the 3-D models and used to quantify changes between surveys.

All the presented works do not take into account the possibility to estimate the crowd of a beach. In this article, real time collected data on environmental parameter and the crowding level, together with users' information (e.g., position, desired activities, and the number of people) are processed to suggest where to go in order to maximize their experience.

B. Crowd Detection

Crowd analysis allows to collect information of a specific physical area, such as density estimation, motion detection, tracking, and behavior recognition [25]. The most used technique for achieving it is based on computer vision, although it can also be done with the help of other sensing systems like smartphone concentration [26] or RFID detection [27]. In this article, we focus on crowd detection through image analysis, since it is the most suitable for our scope.

Image analysis directly depends on the considered location where information are collected. In particular, outdoor analysis shows more challenging problems related to noise generating phenomena like rain, shadows, fog, or sunlight. Moreover, the image processing can be performed considering a single image or sequences. In the second case, flow analysis, tracking, and other methods can be used to extrapolate additional information, as in [16] and [17]. None of the two papers considered the possibility to collect and use also information related to the coastal erosion. In [18], a method to estimate the crowd density by a frame-to-frame approach is presented. In this article, this method has been improved, carrying out a faster and lightweight process that assures less computational operations, taking into account single snapshots of the monitored beaches. In [19], a system that monitor and check the congestion traffic and evaluate how to improve the mobility to reach easily accessible beaches is described. The evaluation of traffic flow does not allow, if considered alone, to obtain an effective evaluation of the real time occupational status of a specific beach. IoT and big data opened a new way to gather devices and data for new crowd management mechanisms [20], [21]. In [22], a novel visual IoT architecture based on smart video analysis, economic transmission, and crowd coordination is presented. Shibata and Yamamoto [23] presented a density observation system able to evaluate people crowd measuring power of cellular communications and processing them using machine learning techniques. The prediction of a crowd formation is another challenging topic. In [24], a feedback system that collects current crowd density is presented, which can process these data to suggest preventive correction (e.g., redirecting people in less crowded places).

Differing from these previous methods, our proposed system also collects data on the coast and, exploiting the advantages of IoT systems and machine learning techniques, is able to react in real time involving users.

Compared with all described previous works, the proposed monitoring system is focused on increasing tourist experience and preserving the coastal ecosystem exploiting both environment, crowd level, and collected users data. Our system relates results obtained by a double "procedure" where natural and social collected data are processed to evaluate how to intervene in real time. Table I summarizes the main differences among previous works and the proposed, in terms of the following main key aspects.

1) *Geosensing:* Capability to collect geological information.
2) *Remote Sensing:* Capability to collect data on the sur- rounding environment.
3) *Image Processing:* Information obtained managing and elaborating the collected images.
4) *Crowd Evaluation:* Capability to estimate the crowding level of a monitored area.
5) *Motion Detection:* Ability to take into account and acquire additional information by considering the motion of people, vehicles, or devices.
6) *Traffic Evaluation:* Capability to use collected data to evaluate and/or improve traffic flow in real time.
7) *Density Estimation:* Capability to perform a crowd density evaluation.
8) *Machine Learning:* Ability to learn and to react by continuously acquiring new information.
9) *IoT:* Use of IoT architectures to reach desired tasks.
10) *Privacy by Design:* Analysis and management of data

As shown in the table, our proposed system encloses all the considered aspects, being able to react in real time by processing all the collected data, protecting sensible data, and also involving users.

Moreover, the use of the innovative SIoT platform allows:

1) to integrate the proposed system with other smart city services useful to improve the way of living in a city (e.g., in terms of traffic of vehicles);
2) scalability in order to foresee new devices and technologies useful to improve the performance of the beach monitoring system.

TABLE I¶
RELATED WORKS—COMPARISON¶

Key Aspects	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	[21]	[22]	[23]	[24]	Proposed Work
Geo Sensing	●		●	●											●
Historical Statistics	●														●
Remote Sensing	●			●											●
Image Processing	●	●	●	●	●	●	●	●		●	●				●
Crowd Evaluation						●	●	●	●	●	●	●	●	●	●
Motion Detection									●					●	●
Traffic Evaluation						●	●		●					●	●
Density Estimation														●	●
Machine Learning													●		●
Internet of Things										●	●	●			●
Privacy By Design															●

III. SOCIAL IOT ARCHITECTURE

A social-oriented approach within the IoT paradigm to man- age huge numbers of heterogeneous devices has been recently proposed to support services and applications dedicated to distributed objects and networks [28]. The SIoT concept, which is intended as a social network where every node is an object capable of autonomously establishing the relationships with other things [29], was formalized in [9], with the definition of a set of rules to establish relationships between objects.

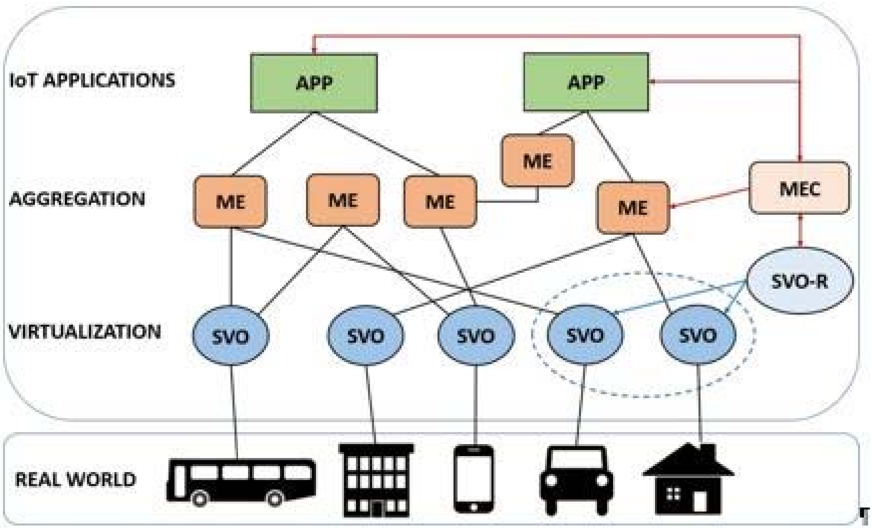
The SIoT contemplates five types of social relations.

1) *Ownership Object Relationship (OOR):* It is created between objects owned by the same owner.
2) *Co-Location Object Relationship (CLOR):* It is created between devices located in the same place.
3) *Parental Object Relationship (POR):* It is created between objects built by the same manufacturer, identified by the same model, vendor, and production batch.
4) *Co-Work Object Relationship (CWOR):* It is created between objects that share experiences in the same workplace.
5) *Social Object Relationship (SOR):* It is created as a con- sequence of frequent encountering between objects, as it happens for humans (e.g., between smartphones of students attending the same class).

These relationships are created and updated on the basis of objects features (e.g., type, computational power, mobility capabilities, or brand) and activities. The model proposed in this article relies on a cloud-based SIoT platform, named Lysis [30]. The main functionalities of the Lysis platform are shortly described in the following section.

A. Lysis Platform

In [31], the virtual object (VO) concept was presented for the first time, defined as the digital counterpart of a physical object in order to provide to users all its potentialities, allowing to collect, process, and exchange information with other objects using the Internet. Lysis is a four-layer architecture SIoT platform based on VOs, as depicted in Fig. 1.



1) *Real World Layer:* It is the lowest layer and includes real world objects (RWOs) that are real physical objects capable of collecting and sending information. The RWOs are able to access the platform via direct links to the Internet, while other resource-constrained objects cannot do this directly but must rely on gateways (GWs).
2) *Virtualization Layer:* It directly interfaces with the real world layer and is populated by the digital counterpart of the RWOs, i.e., social virtual objects (SVOs), which are VOs with socialization capabilities. The heterogeneous nature of real entities leads to a differentiation of RWOs in terms of a semantic description of capabilities and resources. A hardware abstraction layer (HAL) between an RWO and its SVO is in charge to create a secure point-to-point communication (encrypted). A social identity is added to the SVOs on the Lysis plat- form. Indeed, all the social relations and the related functionalities defined by the SIoT paradigm are implemented and maintained in this layer.

3) *Aggregation Layer:* It combines several SVOs thanks to extended capabilities called micro engines (MEs). The ME is a mashup of one or more SVOs and other MEs that implements part of the logic application performed at the upper layer. In each ME, the output for a request coming from an application can be reused to serve requests from different applications that require the same information or service to save bandwidth and CPU. Information from multiple SVOs on the basis of patterns can be used to ensure a high reusability level.
4) *Application Layer:* It is in charge of providing user- oriented macro services. The deployment and execution of applications makes use of one or more MEs.

Socialization algorithms implemented at the virtualization layer, which are based on interactions among RWOs, allow for the creation of social relations between SVOs. The resulting social graph can be exploited to find the required resources by means of a special SVO, called SVO-root (SVO-R), which is in charge of forwarding the query to its friends as well as friends of friends as shown in Fig. 1. To find the required resources, the application sends a query with the semantic description of the needed resources to the ME controller (MEC). The MEC is in charge of forwarding the query to the social graph of SVOs to get a reply with a list of resources and their access keys. After the acquisition of the required resources, the MEC returns them to the application or allocates them to the ME specified by the application. As it will be discussed in the next section, the possibility to establish social relations among objects is fundamental to implement the different functionalities and services provided by the proposed coastal monitoring system.

IV. COASTAL MONITORING SYSTEM

Fig. 2 shows the framework of the coastal monitoring system, which is completely based on the Lysis platform presented in Section III-A.

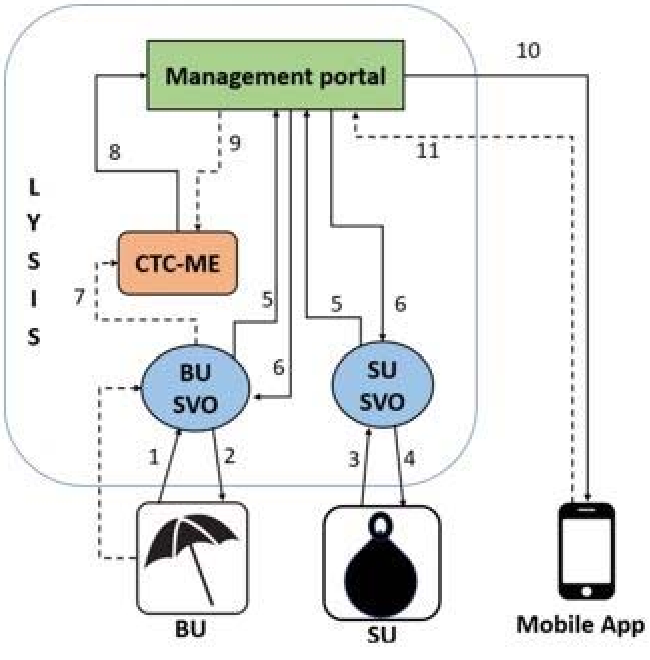


Fig. 2. Framework of the coastal monitoring system. Dashed lines refer to the training period of the classifier model.

The main components are as follows.
1) *Beach Unit (BU):* It is a device installed at the beach, which takes pictures of the beach for crowd detection and measures the relevant beach environmental parameters, i.e., air temperature and humidity, wind direction and strength, and UV radiation.
2) *Sea Unit (SU):* It is a device installed inside a buoy that floats in the sea in front of the beach. The SU measures the relevant water parameters, i.e., temperature, limpidity, pH, and the motion of the waves.
3) *Social Virtual Objects:* The BU SVO and SU SVO are the virtual counterpart of the BU and SU, respectively. These SVOs are created and managed by the virtualization layer of Lysis. By means of the SVOs, Lysis allows the communication between the BU and SU with the management portal.

4) *Crowd Trainer Classifier Micro Engine (CTC-ME):* An ME in charge to train the classifier model for crowd detection. There is one CTC-ME instance for each different beach. The configuration of a new CTC-ME instance is started by the Management portal, which sends the resource request to the MEC. The training of the classifier model is implemented using both beach pictures and voluntary feedback provided by people at the beach. The latter are considered as the ground truth due to the subjective nature of the perception of the beach crowd density.
5) *Management Portal (MP):* It is the Lysis application that provides a user interface to the developers to implement the following actions: a) visualize the data collected by the BUs and SUs with graphical dashboards; b) manage the sampling frequency of BU and SU for data acquisition; and c) manage the CTC-ME and request a new training for the classifier model.
6) *Mobile App (MA):* It is a mobile application that allows mobile users to access to a list of beaches and to visualize real-time beach information collected by the coastal monitoring system. The MA is presented in detail in Section VI-C.

The actions among the coastal monitoring system components, illustrated in Fig. 2, are described in the following.
1) The BU sends the beach environmental data and the result of the beach crowd evaluation to the BU SVO.
2) The BU receives updates regarding the crowd classifier model and the sampling frequency to be set for environmental measurements.
3) The SU sends the seawater parameters to the SU SVO.
4) The SU receives updates regarding the sampling frequency to be set for water parameter measurements.
5) The data collected by the BU SVO and SU SVO is sent to the MP.
6) Updates regarding the crowd classifier model and the sampling frequency to be set for environmental and water measurements are sent to the BU and SU SVOs.
7) Pictures of the beach are sent to the CTC-ME (only during the training period).
8) Updates regarding the crowd classifier model are sent to the MP.
9) Feedback provided by people at the beach regarding beach crowd evaluation are sent to the CTC-ME as ground-truth values (only during the training period).
10) Beach and sea information are sent to the MA
11) Feedback provided by people at the beach regarding beach crowd evaluation are sent to the MP (only during the training period).

The crowd classifier model trained by the CTC-ME is finally installed on the BUs, which can run it to evaluate the beach crowd density based on the taken beach pictures. During the classifier training period, selected people are asked to send feedback regarding the beach crowd evaluation when they are detected at a beach monitored by the proposed system. However, this requires the closeness event between the user's smartphone and the BU to be satisfied as better explained later.

A. SIoT-Based Actions

When users installs the Mobile App into their smartphone, a smartphone SVO is created at the Lysis virtualization layer. The smartphone SVOs (as all the SVOs) provide the socialization functionalities foreseen in the Lysis architecture and needed to create social relations. Therefore, each BU searches for smartphones in the surrounding to establish a SOR relation- ship. Indeed, as explained in Section III, the SOR is created as a consequence of frequent encountering between objects, which in this case are the BU and the user's smartphone. The established SOR between the BU and the smartphone allows different actions between these components.
1) *Feedback About Beach Crowd Evaluation:* When the BU takes a picture of the beach, this is sent to the CTC-ME through the BU SVO. Then, the CTC-ME asks the users owners of the smartphones being part of the social network to provide a feedback regarding the level of beach crowd perceived in that moment. This information will be used by the CTC-ME as a ground- truth value for training the classifier model. Fig. 3 illustrates the establishment of the SOR relationship between the smartphones SVOs (SP SVOs) and the BU SVO, which is due to the detection of the closeness event between the BU and the smartphones.
2) *Alerts and Information to Users:* The SOR relationship established between the BU SVO and the SP SVO is configured so as to provide alerts and information to the nearby friends smartphones. For example, it can warn users about the high intensity of UV radiation or about a dangerous wind intensity.

3) *List of Near Beaches Ordered by Crowd Density Level:* The MA exploits the searching process through the social graph of SVOs (starting from the user SP SVO) so as to find the position of the listed beaches. The MEC executes the SVO search process through the SVO-R of the user who started the MA. The achieved resources are sent back to the MA. The search query provides the description of the required resources. Since it is required by Lysis, the query is passed to the MEC in JSON format and it includes the following:
a) the key to verify the access permissions (if different from the public);
b) the maximum number of requested resources
(*limit*);
c) the depth of search in the social graph (*hop*);
d) the geographic area and a description of the resources in text format in the *description* parameter;
e) the type of relationship which can be exploited by the SVO search process, specified in the *relation- ship* field.

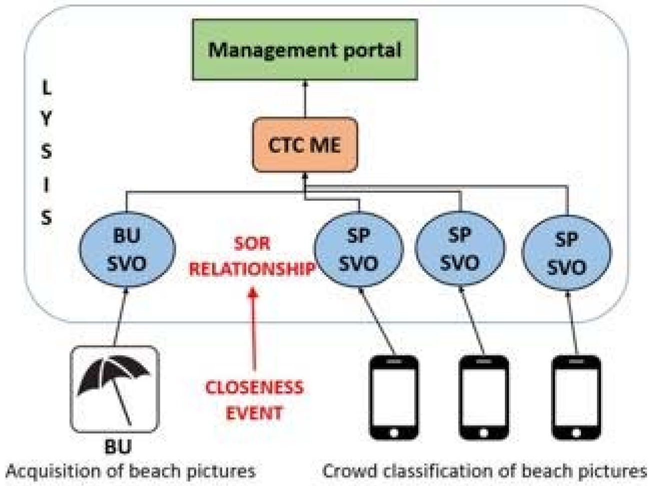


Fig. 3. Establishment of the SOR relationship between the smartphone SVOs and the BU SVO.

B. Privacy by Design

Objects raise issues relating to the processing of personal data and to the protection of the persons to whom the information refers. From objects, it is possible to track people. The risk is very high because with IoT the behavioral patterns of each human person could be concentrated in largest databases, from which information can be obtained, even very confidential, about the lives of people to be used for illicit purposes. The rules to protect personal data from unlawful use are today contained in the EU Reg. 2016/679 [32], general data protection regulation (GDPR), which is characterized by the attention that is placed on the accountability of data controller and processor date.

In this regard, the article 25 of the GDPR establishes the rule "data protection by design and by default." According to this rule, before starting a processing of personal data it is necessary to carry out a context analysis (i.e., of the state-of- the-art and risks for the rights and freedoms of natural persons) and adopt appropriate technical and organizational measures aimed at the concrete protection of personal data. With GDPR, privacy becomes a design constraint and, as a result, protection measures must be implemented by default [33]. The system outlined by the European legislator is based on the assessment of risks (i.e., for the rights and freedoms of natural persons) deriving from the specific activities of processing personal data; consequently the GDPR impacts on the IoT theme at least in two principal aspects: 1) risk analysis and 2) impact assessment.

The article 32 of the GDPR indicates the parameters to be used for the assessments of risks, which are "the state-of-the- art, the costs of implementation and the nature, scope, context, and purposes of processing as well as the risk of varying likelihood and severity for the rights and freedoms of natural persons." Besides these parameters, the data minimization principle should also be taken into account to select the appropriate technical measures to limit the assessed risks. The data minimization principle establishes that "only such data shall be processed as adequate, relevant and not excessive in relation to the purpose for which they are collected and/or further processed”. The data controller must comply with these criteria in all the processing phases: in the development, design, collection, selection, and use of personal data and always in the light of a careful analysis of the specific reference context.

With regard to the proposed coastal monitoring system, privacy by design and privacy by default analysis has been evaluated. The “purpose” of data treatment (beach images in this case) is to evaluate and monitor the crowd level of the beach. Therefore, on the basis of the data minimization principle, the following are the implementation actions that have been taken: 1) the resolution of the pictures of the beach has been automatically decreased in order to make people unidentifiable; 2) the pictures of the beach were solely used to train/refine the classifier model and then deleted from the server after 24 h; and 3) an anonymization procedure has been implemented to disconnect the acquired information from humans. In other cases, a pseudonymization could be sufficient because people are in a context in which it may be necessary, in the aftermath, to associate the personal identity to information. The data controller must always minimize the processing of personal data, give maximum transparency on the purposes and methods of processing personal data, allow the data subject to control the processing by making the rights provided by the regulation easily and effectively exercizable. The legal aspects of IoT are extended far beyond personal data, because it belongs to the world of new technologies whose development is based on the data of all types and not just personal ones. In this regard, on October 4, 2018, the EU Regulation 2018/1807 [34] was approved, which uniformly regulates the free circulation of nonpersonal data within the European Union (EU) and represents the first concrete step toward the elimination of territorial barriers that hinder the development of data-based technologies such as IoT. The new Regulation defines its scope of application with regard to non- personal (i.e., electronic) data, expressly leaving aside all the provisions of the GDPR.

For reasons of consistency with other EU regulations, non- personal data is defined as “data other than those defined by article 4 of the EU regulation 2016/679”: consider, for example, data relating to business-to-business (B2B) economic transactions or data generated by sensors that monitor the operation of industrial machinery. The EU Regulation 2018/1807 introduces the general principle, of free circulation of non- personal data between Member States, with which companies (i.e., public and private) are guaranteed to be able to freely choose the place to process or store data and legitimize restrictions only if adopted in accordance with public and national security requirements. From a practical application point of view, the coordination between the two European Regulations on the circulation of data will not always be easy. As already stated, the application distinction of one or the other is given by the correct identification of the information being processed. Therefore, some cases could arise, such as those concerning pseudonymized or anonymized data, need a particular level of attention for their correct classification.

V. IMPLEMENTATION DETAILS

In this section, we provide the implementation details for the BU and the SU presented in Section IV.

A. Beach Unit

The BU is mainly based on a Raspberry Pi 3 electronic board. Table II details the main hardware and sensors that compose the BU. The pictures of the BU prototype and of its installation at the monitored beach are shown in Fig. 4. We used a camera box as a container for the whole system, that comprises a Raspberry Pi, a vent, a temperature and humidity sensor (DHT), a camera, a 4G LTE USB stick, and the power supply. The vent was used to prevent the glass to be fogged. The camera captures images of the beach, that are processed by the Raspberry running Raspbian OS and Python Open CV. The 4G LTE USB stick provides the Internet access to the system, so that the BU can communicate with its SVO. A battery was not needed since the pole on which we installed the BU was already provided the with power source. However, there is space for a small battery within the BU’s box. Outside the camera box, we installed a wind speed and direction sensor as well.

B. Sea Unit

This unit consists of a buoy, anchored 50 m from the seashore, equipped with Arduino MKRFOX1200. Table III details the main sensors used in the SU, which is shown in Fig. 6. The 3-D MEMS LSM303AGR accelerometer is used to monitor the height and period of the wave. For the direction of the wave, we used the gyroscope

3-D MEMS LSM6DSL and a particular “fin” to allow an accurate measurement. Water turbidity (DFRobot Turbidity Sensor v1.0) and temperature (DS18B20) are monitored as well; these sensors are shown in Fig. 7.

TABLE II
BU–Hardware and Sensors

HARDWARE	FUNCTIONALITY
Camera box	Contains the camera, board, and sensors of the beach unit
Raspberry Pi 3 model B+	Single-board computer 1.4 GHz 64-bit quad-core processor
Power supply 15W 5V 3A	Supplies electric power to Raspberry and sensors
MicroSDHC 16 GB	Storage for OS, libraries, and user programs
Raspberry Pi 8Mp camera	Image sensor custom designed add-on board for Raspberry Pi
Weather station (WSTX20)	Wind direction and wind speed sensor
Temperature and umidity sensor (DHT11)	Measures the atmospheric humidity (%) and temperature (Celsius)
UV Light Sensor (VEML6075)	Senses UVA and UVB light
USB 4G key	Provides data connection to send the real-time data sensor

The main purpose of the SU is to collect data from the sensors and send this data to the cloud, with minimal energy consumption. Therefore, the design choice fell on a low power wireless area network (LPWAN) technology that offered coverage in the considered area, i.e., Sigfox. Sigfox offers a software-based communications solution, where all the network and computing complexity is managed in the cloud, rather than on the devices, and it drastically reduces energy consumption and costs of connected devices [35]. Furthermore, as shown in Fig. 5, SigFox offers excellent coverage in the region of interest.[1]More specifically, the Sardinia island is represented in purple whereas in cyan it is defined whether a point is covered or not. Coverage information is issued by Sigfox Global Communications Service Provider. Sigfox provides a link quality indicator (LQI) based on received signal strength indicator (RSSI), number of stations that received a message (i.e., receiver redundancy), and RC zone due to the difference between the radio configurations (RCs). The LQI limits are equal to RSSI ≤ −135 dBm and RSSI ≤ −135 dBm for RC1-RC3-RC5 and RC2-RC4, respectively, [36]. This aspect has proved to be fundamental in the choice of the wireless communication standard used in the communication of data transmitted by the SU. A second aspect not less important than the previous one, is that Sigfox is part of the LPWAN, a particular type of wireless wide area network designed to allow long range communications at a low bit rate sensors operating on a battery. The low power and low bit rate distinguish this type of network from a classic wireless WAN designed to connect users, and carry more data, using more power. Commonly, the LPWAN data rate ranges from 0.3 to 50 kb/s per channel [37]. As shown in Fig. 8, three BUs and a SU were installed in the first three areas on a 7 km beach in the city of Cagliari, named Poetto, which collected data from late summer 2017. The buoy is fixed with an anchor at coordinates 39°11’44.24” N 9°9’42.63” E.

TABLE III
SU–Hardware and Sensors

HARDWARE	FUNCTIONALITY
Board Arduino MKRFOX1200	Combines the functionality of the Arduino Zero and Sigfox connectivity
Adapter MKR/Arduino UNO	Turns the Arduino UNO form factor based project into a MKR based one
Power supply	2 x Li-ion 18650 model battery
Magnetometer 3D MEMS LSM303AGR	Measures the magnetic field dynamic range of ± 50 gauss
Accelerometer 3D	Linear acceleration full scales ±2g ±4g ±8g ±16g
Gyroscope 3D MEMS LSM6DSL	Measures the direction in degrees
Water temperature sensor DS18B20	Temperature range -55°C to 125°C with accuracy of ± 5°C
Gravity Analog Turbidity Sensor	Detects water quality by measuring level of turbidity in Nephelometric Turbidity Unit (NTU)
Analog pH Sensor/Meter Kit V2	Measures the pH of the solution and reflects the acidity or alkalinity

[1] https://www.sigfox.com/en/coverage

(a) (b)

Fig. 4. BU prototype: (a) internal view and (b) BU installed in the monitored Poetto beach.

Fig. 5. Cagliari area Sigfox coverage.

Fig. 6. SU.

Fig. 7. SU with water turbidity in nephelometric turbidity unit (NTU) and temperature sensors.

Fig. 8. Cagliari–Poetto shoreline area with 3 BUs and 1 SU.

VI. EXPERIMENTAL RESULTS

The experimental evaluation of the coastal monitoring system concerned the testing of the whole system and, in particular, the evaluation of the performance of the crowd classifier model, which is provided in Section VI-A. Moreover, the data collected with the system allows for performing data analysis to extract valuable knowledge, as discussed in Section VI-B. Finally, in Section VI-C, we present the mobile app developed for citizens and tourists.

A. Crowd Evaluation

The crowd classifier model introduced in Section IV has the objective to evaluate the crowd density of the beach during the day. It is mainly based on a machine learning classifier which estimates the crowd density of the beach based on a picture of the beach. Therefore, to train the algorithm, we collected a data set of pictures of the Poetto beach in Cagliari, Italy, which were taken by the camera of the BU installed at that beach. The camera took a photo of the beach each half-hour from 8 A.M. to 8 P.M. during the months of June, July, August, and September, which are the most frequented by people, for a total of about 1600 pictures per year.

We considered three levels of crowd density.

1) *Low Crowd Density (LCD):* Some people are in the beach but most of the beach is empty.
2) *Medium Crowd Density (MCD):* Many parts of the beach are occupied but there is still some empty space.
3) *High Crowd Density (HCD):* Most of the beach is occupied.

To assign the labels to the collected pictures, we asked 20 people to classify the pictures using the three aforementioned classes. Then, we assigned the mode class (i.e., the most selected class by the people) to each picture as the ground-truth value.

The proposed crowd classifier model implements the following steps.

1) A mask is applied to the picture of the beach to remove the parts which are not of interest for classification.
2) Local binary patterns (LBP) features are extracted from the picture, which are commonly used as visual descriptors for classification in computer vision [38].
3) A support vector machine (SVM) classifier based on the “one-against-one” classification strategy for multiclass problems is used for picture classification.

The training/validation experiments followed a fivefold cross-validation configuration where 70% of the data set was used for training whereas the remaining 30% for validation.

The training set was equally composed of pictures from the three considered classes (i.e., 33% from LCD and HCD, 34% from MCD). The performance of the crowd classifier model, which are summarized in Table IV, are evaluated in terms of accuracy, precision, and specificity.

TABLE IV
PERFORMANCE OF THE CROWD CLASSIFIER MODEL

Metric	LCD	MCD	HCD
Accuracy	94.30%	82.94%	87.32%
Precision	89.62%	70.59%	93.24%
Specificity	93.29%	82.41%	97.28%
Overall accuracy		82.94%	

From the results, it can be noticed that the crowd classifier model performs better for LCD and HCD classes, with an accuracy of 94.30% and 87.32%, respectively. On the other hand, the recognition of the MCD is more difficult, with an accuracy of 82.94% which is still a good result. This difference may be due to the fact that it is easier to recognize extreme situations, such as LCD and HCD than an intermediate situation (MCD). By comparing LCD and HCD, the former achieves the best result probably because a free beach is more easy to be recognized than a full occupied beach, which may be confused with a half occupied beach. Precision and specificity metrics achieved similar results performing better for LCD and HCD than MCD, with HCD achieving best performance in these cases. However, it must be highlighted that the crowd density of a beach is not an objective measure but can vary from subject to subject depending on the different personal perceptions of the people. Therefore, even if the achieved results could be improved by implementing an online training or by enhancing parameters tuning, the achieved performance are already good enough to provide an indication of the crowd density occupation of the beach to people who want to reach it.

Finally, we want to highlight that in the current version of the system we only considered three levels of crowd density for the following main reasons.

1) The main objective of the crowd evaluation process is to avoid beaches to be overcrowded for environmental, sustainability, mobility, and safety reasons. Three levels were then considered enough to warn people not to reach the beaches evaluated as highly crowded.

2) Beach crowd evaluation is not straightforward as there are no standard metrics to measure it. Also, the perceived crowd level may change from subject to subject, in particular, when middle crowd levels must be evaluated (people may have different perception of medium-low and medium-high crowd occupation that may create confusion). Therefore, based on the aforementioned crowd evaluation objectives, we minimized the selectable crowd levels to simplify the subjective evaluation.

3) In the current version of the system, we implemented the image classifier with an SVM, which is a simple classifier based on finding a splitting boundary from image points. However, this provides good results even with a limited number of images. But this current choice does not prevent future upgrade of the crowd classifier, which can be replaced with a deep learning system, for example, which provides a complete solution for complex problems, such as object recognition, object segmentation, and image classification. Using such a system could even allow to accurately classify more than three crowd levels. However, deep learning models require a huge number of images to be trained, which means increased time for the system to work. This is an important future upgrade for the presented system but not the main aim of the proposed manuscript.

B. Data Analysis

The proposed system was installed in the middle of 2017 at the Poetto beach and from that day it monitored the crowd density of the beach as well as some beach environmental parameters, such as temperature, humidity, and wind speed. Therefore, thanks to this data set it is possible to perform data analysis techniques to extract valuable knowledge that may help the city administration to take strategic decisions. For example, by monitoring the crowd density of the beach it is possible to understand which are the days, the hours, and the beach areas preferred by people and then enhance public transport for the identified times/locations to mitigate traffic congestion. As an example of knowledge extracted from data, Fig. 9 shows the average daily crowd density monitored at the Poetto beach during July and August 2018. It can be seen that, on average, from 10 A.M. to 18 P.M. the beach tends to be quite occupied, and particularly highly occupied from 12 A.M. to 16 A.M., which is the peak time. As a consequence, public transport services during these times should be enhanced.

As a further example, Fig. 10 shows the daily temperature monitored at the Poetto beach on July 4, 2019. By monitoring each day the temperature, statistics can be computed that can suggest which are the hottest hours to be avoided by people or which require people to be more careful.

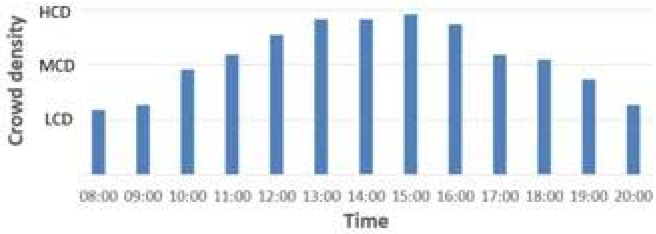


Fig. 9. Average daily crowd density monitored at the Poetto beach during July and August 2018.

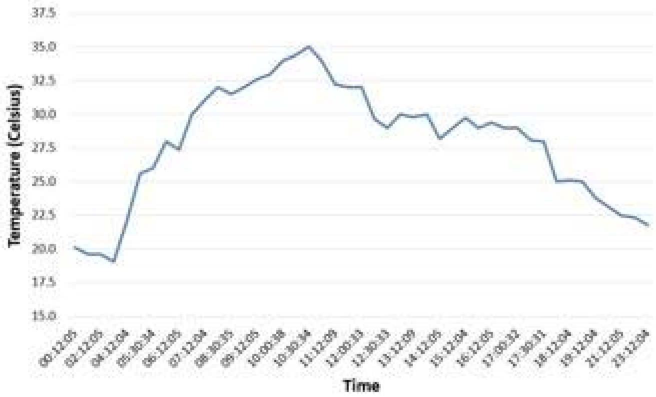


Fig. 10. Daily temperature monitored at the Poetto beach on July 4, 2019.

C. Mobile Application

The MA is a Lysis-type App, which runs on Google App Engine and is available on the Lysis market. People can install the MA on Android devices.

The development of the MA needed the development of different applications that have been carried out with different programming languages.

1) The back-end part was developed in Python with the use of the webapp2 framework.

2) Interfaces were carried out with the Lysis platform through its API for reading data from the sensors.

3) The front-end is developed using HTML, CSS, and JavaScript on top of the bootstrap framework.

4) Applications are cloud web-services.

5) The graphic interface of the MA is rendered on the smartphone through the Lysis App, which is a software container for mobile devices.

At the start, the splash screen is presented while the MA initializes, finds the current location of the smartphone via GPS, and retrieves the five most popular beaches in the vicinity [Fig. 11(a)], i.e., those that have had the highest average crowd value in the last month. The first screen shows the logo at the top of the toolbar, a sidebar type menu at the top right, and two cards.

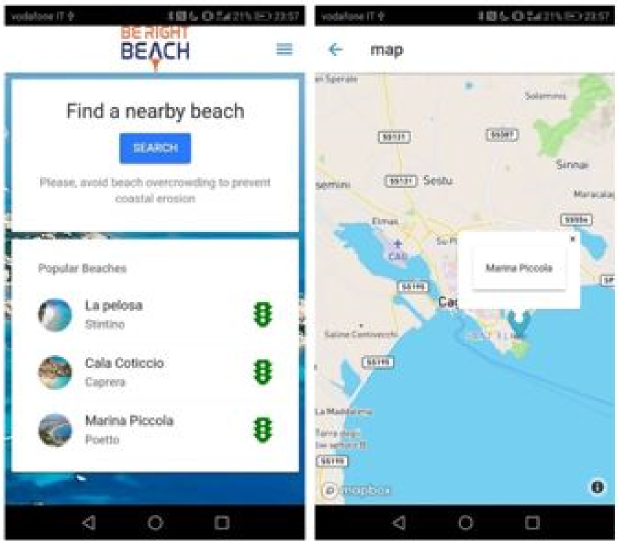
1) A card with the slogan of the system and the button to start searching for monitored beaches nearby.

2) The second one with a list of the most popular beaches.

For each is shown the representative image, the name and an icon that indicates the current crowding level.

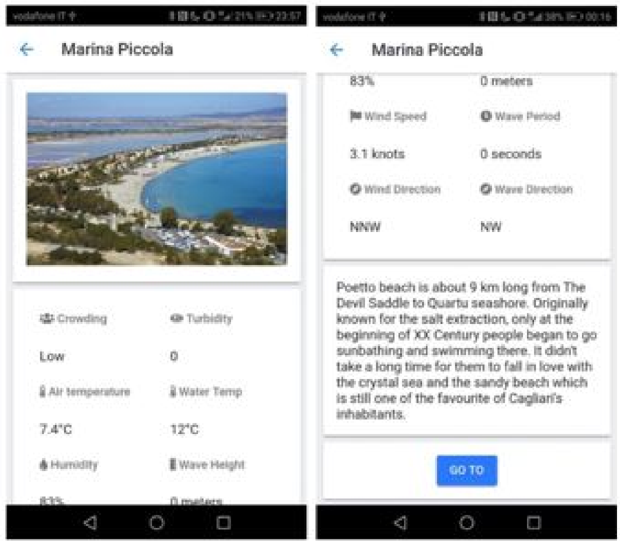
Clicking on the “Search” button, the App requests the list of beaches from the platform and displays them on the map [Fig. 11(b)]. Each marker is combined with a pop-up window which opens the descriptive screen of the relative beach. The map is provided through the Mapbox service which requires a registration to obtain the API key for access to the service. The beach description screen has a representative image

dynamically loaded from the central platform and two columns of sensor data [Fig. 12(a)]. In the left column, the values sampled by the sensors present in the ground station are shown, which for this prototype include the following:
1) crowd sensor;
2) air temperature;
3) humidity;
4) average wind speed;
5) wind direction.
In the right column, the values of the sensors sampled from the buoy are shown.
1) water temperature;
2) water turbidity;
3) wave height;
4) wave period;
5) wave direction.
The button at the bottom of the screen activates a pop- up for choosing the navigation application from among those installed to reach the selected beach [Fig. 12(b)]. The MA, through push notifications, is able to provide a crowd assess- ment functionality to the user in order to make the labeling of the images as transparent as possible.



(a) (b)

Fig. 11. MA: beaches overview. (a) Home screen: list of the nearby popular beaches and their crowding status. (b) Map of the nearby monitored beaches.



(a) (b)

Fig. 12. MA: beach details. (a) Beach description screen with sensor data. (b) "GO TO" button activates the navigator.

VII. CONCLUSION

In this article, a coastal monitoring system based on the SIoT was presented. Thanks to social relationships, sensors, cameras, smartphones, and other devices located in the beach area are able to cooperate in order to estimate beach over- crowding and to acquire local environmental information (e.g., temperature, wind intensity, and direction, or UV intensity).

Users' feedback is also considered to help in creating training sets to allow the newly developed algorithm in monitoring procedure.
The proposed system was installed at the Poetto beach of Cagliari (Italy), monitoring the crowd density of the beach and environmental parameters from 2017. Training and validation tests were carried out on the crowd classifier model, evaluating its performance in terms of accuracy, precision, and specificity. Results showed how the classifier model performs better for low and high crowd density condition, with an accuracy of 94.30% and 87.32%, respectively.

Moreover, the authors developed a mobile application to make all the collected information available and useful for different types of users. Thanks to the collected data, time and location preferences can be evaluated helping police and public transportation systems to better supervise traffic congestion, but also tourists and citizens to select the best option both in terms of travel duration and crowding level of beaches.

ACKNOWLEDGMENT

A preliminary version of the system presented in this article won the first prize at the Hackathon competition during the IoT week held in Geneva on June 6–9, 2017.

REFERENCES

[1] Intergovernmental Panel on Climate Change (IPCC), *Special Report: Global Warming of 1.5° C*, Geneva, Switzerland, 2018. [Online]. Available: https://www.ipcc.ch/sr15/
[2] European Environment Agency (EEA). (2006). *EEA Briefing 3/2006*. [Online]. Available: https://www.eea.europa.eu/publications/bri efing_2006_3
[3] *MITOMED: Models of Integrated Tourism in the Mediterranean*. Accessed: Jun. 16, 2019. [Online]. Available: http://www.medmaritimeprojects.eu/section/mitomed
[4] United Nations Environment Programme (UNEP), *Coordinating Unit for the Mediterranean Action Plan—Secretariat to the Barcelona Convention and its Protocols*, Nairobi, Kenya, 2019. [Online]. Available: http://web.unep.org/unepmap/
[5] Q. Zhang, L. T. Yang, Z. Chen, P. Li, and F. Bu, “An adaptive dropout deep computation model for industrial IoT big data learning with crowd- sourcing to cloud computing,” *IEEE Trans. Ind. Informat.*, vol. 15, no. 4, pp. 2330–2337, Apr. 2019.
[6] F. Zhang, M. Liu, Z. Zhou, and W. Shen, “An IoT-based online monitoring system for continuous steel casting,” *IEEE Internet Things J.*, vol. 3, no. 6, pp. 1355–1363, Dec. 2016.
[7] S. Dhingra, R. B. Madda, A. H. Gandomi, R. Patan, and M. Daneshmand, “Internet of Things mobile—Air pollution monitor- ing system (IoT-Mobair),” *IEEE Internet Things J.*, vol. 6, no. 3, pp. 5577–5584, Jun. 2019.
[8] A. M. Zarca *et al.*, “Security management architecture for NFV/SDN- aware IoT systems,” *IEEE Internet Things J.*, vol. 6, no. 5, pp. 8005–8020, Oct. 2019.
[9] L. Atzori, A. Iera, and G. Morabito, “SIoT: Giving a social structure to the Internet of Things,” *IEEE Commun. Lett.*, vol. 15, no. 11, pp. 1193–1195, Nov. 2011.
[10] L. Atzori, R. Girau, V. Pilloni, and M. Uras, “Assignment of sensing tasks to IoT devices: Exploitation of a social network of objects,” *IEEE Internet Things J.*, vol. 6, no. 2, pp. 2679–2692, Apr. 2019.
[11] M. F. Bruno *et al.*, “Integration of multitemporal SAR/InSAR techniques and NWM for coastal structures monitoring: Outline of the software system and of an operational service with COSMO-SkyMed data,” in *Proc. IEEE Workshop Environ. Energy Struct. Monitor. Syst. (EESMS)*, Jun. 2016, pp. 1–6.
[12] H. Ding, H. Lin, and R. R. Li, “Remote sensing-based dynamic study of nature reserve in Panjin red beach remote sensing-based dynamic study of nature reserve in Panjin red beach,” in *Proc. Progress Electromagn. Res. Symp. (PIERS)*, Shanghai, China, Aug. 2016, pp. 1527–1531.
[13] B. Jena, D. S. Kumar, and K. Kintada, “Operational strategy to monitor coastal erosion in tropical areas,” *J. Ocean Climate Sci. Technol. Impacts*, vol. 8, no. 3, pp. 135–143, May 2017.
[14] A. Papakonstantinou, M. Doukari, and K. Topouzelis, “Coastline change detection using unmanned aerial vehicles and image processing,” *Fresenius Environ. Bull.*, vol. 26, pp. 5564–5571, Sep. 2017.
[15] K. Pikelj, I. Ružic´, S. Ilic´, M. R. James, and B. Kordic´, “Implementing an efficient beach erosion monitoring system for coastal management in Croatia,” *Ocean Coastal Manag.*, vol. 156, pp. 223–238, Apr. 2018.
[16] H. G. Ziegler, “Privacy-preserving and IoT-capable crowd analysis and detection of flow disturbances for enhancing public safety,” in *Proc. 5th Int. Conf. Smart Cities Green ICT Syst. (SMARTGREENS)*, Rome, Italy, Apr. 2016, pp. 1–8.
[17] M. Marsden, K. McGuinness, S. Little, and N. E. O’Connor, “ResnetCrowd: A residual deep learning architecture for crowd counting, violent behaviour detection and crowd density level classification,” in *Proc. 14th IEEE Int. Conf. Adv. Video Signal Based Surveillance (AVSS)*, Lecce, Italy, Aug./Sep. 2017.
[18] M. Fu, P. Xu, X. Li, Q. Liu, M. Ye, and C. Zhu, “Fast crowd density estimation with convolutional neural networks,” *Eng. Appl. Artif. Intell.*, vol. 43, pp. 81–88, Aug. 2015.
[19] M. Alam, J. Ferreira, S. Mumtaz, M. A. Jan, R. Rebelo, and J. A. Fonseca, “Smart cameras are making our beaches safer: A 5G- envisioned distributed architecture for safe, connected coastal areas,” *IEEE Veh. Technol. Mag.*, vol. 12, no. 4, pp. 50–59, Dec. 2017.
[20] H. Hassanein, N. Zorba, S. Han, S. S. Kanhere, and M. Shukair, “Crowd management,” *IEEE Commun. Mag.*, vol. 57, no. 4, pp. 18–19, Apr. 2019.

[21] K. Abualsaud *et al.*, “A survey on mobile crowd-sensing and its applications in the IoT era,” *IEEE Access*, vol. 7, pp. 3855–3881, 2019.
[22] W. Ji, J. Xu, H. Qiao, M. Zhou, and B. Liang, “Visual IoT: Enabling Internet of Things visualization in smart cities,” *IEEE Netw.*, vol. 33, no. 2, pp. 102–110, Mar./Apr. 2019.
[23] K. Shibata and H. Yamamoto, “People crowd density estimation system using deep learning for radio wave sensing of cellular communication,” in *Proc. Int. Conf. Artif. Intell. Inf. Commun. (ICAIIC)*, Okinawa, Japan, Feb. 2019, pp. 143–148.
[24] Y. Kawamoto, N. Yamada, H. Nishiyama, N. Kato, Y. Shimizu, and Y. Zheng, “A feedback control-based crowd dynamics management in IoT system,” *IEEE Internet Things J.*, vol. 4, no. 5, pp. 1466–1476, Oct. 2017.
[25] S. H. Y., G. Shivakumar, and H. S. Mohana, “Crowd behavior analysis: A survey,” in *Proc. Int. Conf. Recent Adv. Electron. Commun. Technol. (ICRAECT)*, Mar. 2017, pp. 169–178.
[26] T. Franke, P. Lukowicz, and U. Blanke, “Smart crowds in smart cities: Real life, city scale deployments of a smartphone based participatory crowd management platform,” *J. Internet Services Appl.*, vol. 6, no. 1, p. 27, 2015.
[27] D. Zhang, L. T. Yang, M. Chen, S. Zhao, M. Guo, and Y. Zhang, “Real- time locating systems using active RFID for Internet of Things,” *IEEE Syst. J.*, vol. 10, no. 3, pp. 1226–1235, Sep. 2016.
[28] A. M. Ortiz, D. Hussein, S. Park, S. N. Han, and N. Crespi, “The cluster between Internet of Things and social networks: Review and research challenges,” *IEEE Internet Things J.*, vol. 1, no. 3, pp. 206–215, Jun. 2014.
[29] L. Atzori *et al.*, “Enhancing identifier/locator splitting through social Internet of Things,” *IEEE Internet Things J.*, vol. 6, no. 2, pp. 2974–2985, Apr. 2019.
[30] R. Girau, S. Martis, and L. Atzori, “Lysis: A platform for IoT distributed applications over socially connected objects,” *IEEE Internet Things J.*, vol. 4, no. 1, pp. 40–51, Feb. 2017.
[31] V. Foteinos, D. Kelaidonis, G. Poulios, P. Vlacheas, V. Stavroulaki, and P. Demestichas, “Cognitive management for the Internet of Things: A framework for enabling autonomous applications,” *IEEE Veh. Technol. Mag.*, vol. 8, no. 4, pp. 90–99, Dec. 2013.
[32] *Regulation (EU) 2016/679 of the European Parliament and of the Council—27 April 2016 on “The Protection of Natural Persons With Regard to the Processing of Personal Data and on the Free Movement of Such Data, and Repealing Directive 95/46/EC (General Data Protection Regulation)*,” Eur. Parliament, Brussels, Belgium, 2016.
[33] A. Cavoukian, “Privacy by design: Origins, meaning, and prospects for assuring privacy and trust in the information era,” in *Privacy Protection Measures and Technologies in Business Organizations: Aspects and Standards*. Hershey, PA, USA: Inf. Sci. Ref., 2012, pp. 170–208.
[34] *Regulation (EU) 2018/1807 of the European Parliament and of the Council—14 November 2018 on a Framework for the Free Flow of Non-Personal Data in the European Union*, Eur. Parliament, Brussels, Belgium, 2018.
[35] *Sigfox Technology Overview*, Toulouse, France, 2018. [Online]. Available: https://www.sigfox.com/en/sigfox-iot-technology-overview
[36] *Sigfox Link Quality: General Knowledge*. Accessed: Jun. 16, 2019. [Online]. Available: https://support.sigfox.com/docs/link-quality:- general-knowledge
[37] W. Ayoub, A. E. Samhat, F. Nouvel, M. Mroue, and J.-C. Prévotet, “Internet of Mobile Things: Overview of LoRaWAN, DASH7, and NB-IoT in LPWANs standards and supported mobility,” *IEEE Commun. Surveys Tuts.*, vol. 21, no. 2, pp. 1561–1581, 2nd Quart., 2019.
[38] C. Chen, B. Zhang, H. Su, W. Li, and L. Wang, “Land-use scene classification using multi-scale completed local binary patterns,” *Signal Image Video Process.*, vol. 10, no. 4, pp. 745–752, Apr. 2016

Massimo Farina received the Laurea (M.S.) degree in law from the University of Cagliari, Cagliari, Italy, and the Dottorato di Ricerca (Ph.D.) degree in com- puter law from the University of Bologna, Bologna, Italy.
Since 2006, he has been an Adjunct Professor of computer and new technologies law, Department of Electrical and Electronic Engineering, University of Cagliari. He is a Data Protection Officer with the University of Cagliari and the Coordinator of ICT4Law&Forensics. His research interests are data protection, computer crimes, digital forensics, and juridical protection of software.

Roberto Girau (S'13–M'18) received the M.S. degree in telecommunication engineering and the Ph.D. degree in electronic engineering and computer science from the University of Cagliari, Cagliari, Italy, in 2012 and 2017, respectively. Since graduation, he has been working as a Researcher with the Department of Electrical and Electronic Engineering, University of Cagliari, developing an experimental platform for the social Internet of Things, where he has been an Assistant Professor since 2017. His main research areas of interests are Internet of Things with particular emphasis on its integration with social networks, software engineering, smart cities, and cloud computing.

Alessandro Floris (S'14–M'18) received the M.Sc. degree in electronic engineering and the Ph.D. degree in electronic and computer engineering from the University of Cagliari, Cagliari, Italy, in 2011 and 2017, respectively.
He is an Assistant Professor with the Department of Electrical and Electronic Engineering, University of Cagliari. He was Awarded a research grant from 2011 to 2013 with the Department of Electrical and Electronic Engineering, University of Cagliari. His main research interests include quality of experience, Internet of Things, and smart cities.
Dr. Floris is a member of the Multimedia & Communications Laboratory and the Italian University Consortium for Telecommunications

Matteo Anedda (S'12–M'18) received the B.Sc. degree in electronic engineering and the M.Sc. degree (*summa cum laude*) in telecommunication engineering from the University of Cagliari, Cagliari, Italy, in 2011 and 2012, respectively.
He is currently an Assistant Professor with the University of Cagliari. He was a Visiting Erasmus Student with the University of Basque Country, Bilbao, Spain, in 2010 for eight months, where he has carried out the M.Sc. thesis under the super- vision of Prof. P. Angueira. He was a Visiting Researcher with Dublin City University, Dublin, Ireland, under the supervision of Prof. G. Muntean in 2015 and Universidad de Montevideo, Uruguay, under the supervision of Prof. R. Sotelo in 2016, for seven months each. His research interests are network planning, coverage optimization and optimization algo- rithms, real-time applications, 5G networks and network selection, Internet of Things and smart cities, rate control, mobile device energy consumption and energy efficiency, adaptive multimedia streaming, and heterogeneous radio access environment.
Dr. Anedda has received an Award from the Order of the Engineers of Cagliari for his M.Sc. thesis. He is a member of IEEE Broadcast Technology, IEEE Communications, and IEEE Vehicular Technology Societies.

Mariella Sole (M'15) received the Laurea (M.S.) and Dottorato di Ricerca (Ph.D.) degrees in telecom- munications engineering from the University of Cagliari, Cagliari, Italy, in 2010 and 2014, respectively.
Since 2014, he has been a Research Fellow with the Department of Electrical and Electronic Engineering, University of Cagliari. Her research interests are wireless networks, sensor networks, Internet of Things, and smart cities.

Mauro Fadda (S'11–M'15) received the M.Sc. degree in telecommunication engineering from the University of Bologna, Bologna, Italy, in 2006, and the Ph.D. degree from the University of Cagliari, Cagliari, Italy, in 2013.
He is an Assistant Professor with the Department of Electrical and Electronic Engineering, University of Cagliari. In 2007, he spent one year as a Researcher with National Research Center, Bologna Developing UMTS Mobile-Network Simulation Software. From 2008 to 2009, he was a Researcher with the Research Center of Sardinia in Pula implementing different Web communication applications. From 2014 to 2015, he was a Researcher with the Research Unit of the Italian University Consortium for Telecommunications, University of Cagliari. His main research interests are telecommunications, cognitive radio systems, mobile technologies, and broadcasting systems

Daniele Giusto (S'87–M'90–SM'00) received the Laurea (M.S.) degree in electronic engineering and the Dottorato di Ricerca (Ph.D.) degree in telecom- munications from the University of Genoa, Genoa, Italy, in 1986 and 1990, respectively.
Since 1994, he has been a Permanent Faculty Member with the Department of Electrical and Electronic Engineering, University of Cagliari, Cagliari, Italy, where he became a Full Professor of telecommunications in 2002. His research interests are smart cities, sensor networks and Internet of Things, mobile and professional networks, and digital media.
Dr. Giusto was a member of the IEEE Standard committee from 2007 to 2010 and the Italian Delegate in the ISO-JPEG. He is the Italian Delegate in the ISO-Smart Cities Committees.