Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Beach carrying capacity management under Covid-19 era on the Basque Coast by means of automated coastal videometry

Irati Epelde a,*, Pedro Liria a, Iñaki de Santiago a, Roland Garnier a, Adolfo Uriarte a, Artzai Picón b, Adrián Galdrán c, Jose Antonio Arteche b, Alberto Lago b, Zurik Corera d, Inaki Puga e, Jose Luis Andueza e, Gabriel Lopez e

a AZTI Marine Research, Basque Research and Technology Alliance (BRTA), Herrera Kaia. Portaldeka s/n, 20110, Pasaiako, Gipuzkoa, Spain
b University of Bournemouth, Fern Barrow, Poole, Dorset, BH12 5BB, United Kingdom
c Eusko Jaurlaritza/Gobie, 20004, Donostia, Gipuzkoa, Spain
d TECNALIA, Basque Research and Technology Alliance (BRTA), Parque Tecnológico de Bizkaia, C/ Geldo. Edificio 700, 48160, Derio, Bizkaia, Spain
e Gipuzkoako Forunkaleak, Diputación Foral de Gipuzkoa, Gipuzkoa Plaza, S/N, 20004, Donostia, Gipuzkoa, Spain

* Corresponding author.
E-mail address: iraelde@azti.es (I. Epelde).

https://doi.org/10.1016/j.ocecoaman.2021.105588
Received 20 November 2020; Received in revised form 24 February 2021; Accepted 24 February 2021
Available online 30 March 2021
0964-5691/© 2021 Elsevier Ltd. All rights reserved.

1. Introduction

Beaches are places of leisure and recreation visited by large numbers of people mainly during the summer season. In the coast of Gipuzkoa (Basque Country, Northern Spain), approximately 55% of the total population lives in the coastal area. Besides, the region receives a large number of tourists and sea-users. Tourism accounts for 7.4% of the gross regional income (Eusko Jaurlaritza/Gobie, 2020).

The on-going COVID-19 pandemic is among the most devastating global human epidemics. It not only has become a public health crisis, but it has also negatively affected the global economy (Pak et al., 2020). Recent studies confirmed that the peakiness of the epidemic is strongly shaped by population aggregation and heterogeneity (Pak et al., 2020), hence, quarantine and social distancing are currently employed to control its spread within communities. Following such recommendations, the Gipuzkoa Provincial Council decided to apply preventive measures during the 2020 summer to avoid beach crowding, by fixing a minimum extension of individual occupation of eight square meters of free subaerial beach surface per person (Diputación Foral de Gipuz, 2020). Hence, coastal city councils, as beach managers in their municipalities, had the need to regulate the beach access to limit the beach attendance and ensure the minimum social distance recommended by the health authorities.

Multiple approaches have been conducted to quantify the number of people visiting the beach. The measure of this parameter is fundamental for defining coastal management plans, for example, at the time of identifying the physical carrying capacity of a beach (the number of individuals a beach can physically accommodate) (Da Silva, 2002), or the beach carrying capacity (the quantity and type of visitors that can be accommodated within a beach without unacceptable social...
consequences and negative impact on resources) (Manning and Lawson, 2002). A first distinction can be made between manual and automatic methods. Despite the fact that beach user manual counting only gives information at specific times (or during short periods of time) and no standardized methodology has been proposed, there are still studies that follow such method (King and McGregor, 2012; Dwight et al., 2007). On the other hand, automatic methods based on coastal videometry techniques for determining beach user density (BUD) and their distribution have shown their efficiency providing continuous data from months (Kammler and Schernerski, 2004) to years (Guillén et al., 2008). Although these techniques have been successfully used to investigate on beach user behaviour (Balouin et al., 2014) and to determine beach carrying capacity in real time (Císeros et al., 2016), their benefits to coastal management planning have not been demonstrated yet, as examples of application by beach managers or by beach users are missing.

In Gipuzkoa, a coastal videometry network was developed by the Environment Department of the Provincial Council with the aim of assisting different beach management programs, from long term applications (beach morphology and flooding event monitoring) to daily management for beach safety and for beach carrying capacity control. For this latter application, the real time assessment of beach attendance has been a challenge given the extension of the network (it covers 14 beaches, with 12 stations, along 50 km of coastline).

Automatic methods to count beach users were initially based on the measure of pixel intensity and on ad-hoc filtering techniques (Kammler and Schernerski, 2004; Guillén et al., 2008; Balouin et al., 2014). However, these methods are difficult to parametrize and do not appropriately adequate to different locations and illumination conditions. Recent studies based on machine learning approaches (Gulden, 2018) have delivered more sophisticated image segmentation methods (Hoontout et al., 2015) for beach occupation estimation. However, these methods involve a huge number of highly precise manually segmented training examples that require a statistically significant number of examples, which is prohibitively time-consuming. Therefore, they are not well adapted to be implemented at regional scale. The use of unsupervised segmentation techniques (Guillén et al., 2008) such as the ones based on active contours (Jimenez et al., 2007) represent a popular and very successful class of algorithm (Caselles et al., 1993), that need no manually labelled data. However, they tend to be unreliable, due to the necessity to manually tune many parameters, to adequate the different techniques to the particularities of each problem.

In this paper, in order to overcome these issues, we have adapted our hybrid method from medical imaging segmentation (Bereciartua et al., 2015, 2016) where a modest number of manual segmentations were gathered, from which a coarse segmentation via statistical classification techniques was obtained. This allows us to perform automatic assessment of beach attendance in real time along the coast of Gipuzkoa.

This approach has been applied in the context of COVID-19 and a new methodology for the management of the beach carrying capacity, by means of coastal videometry, has been developed aiming at ensuring the necessary social distance to minimize contact between individuals. This resulted in providing beach occupation information in real time through a web/mobile app to support coastal managers and lifeguards’ decisions, to raise beach user awareness and to help them to reduce displacements to the beach in a conscious way.

2. Methodology
2.1. Study site
Real time beach occupation data were collected from a total of 14 beaches located along the Basque coast (SE Bay of Biscay) during the 2020 summer season. All the studied beaches are located in the Gipuzkoa province (Fig. 1), and all of them are urban beaches with different kind of infrastructures. The beaches in this study belong to 7 different coastal municipalities (in groups of 1–3 beaches per municipality), and they have different characteristics in terms of subaerial beach surface capacity. Due to the length of some of the beaches, or due to specific requests from the municipalities, some beaches have been subdivided into 2 or 3 zones (Z).

![Fig. 1.](image-url) (a) Localisation of the Gipuzkoan coast and of the beaches included in the analysis: (1) Saturraran, (2) Ondarbelzt, (3) Santiago (Deba), (4) Lapari, (5) Itzurun, (6) Santiago (Zumaia), (7) Gaztetape, (8) Malkorbe, (9) Zarautz, (10) Antilla, (11) Ondarreta, (11) La Concha, (12) Zurrriola, (14) Hondarribia. (b-c-d) Oblique images of b) Malkorbe, c) Zarautz and d) Ondarreta beaches obtained from the videometry stations.
The tidal regime is semi-diurnal and has a maximum annual tidal range that exceeds 4.5 m. It is defined as low-mesotidal during neap tides, and high-mesotidal during spring tides (Gonzalez et al., 2004). The beach sediment along the Basque coast is composed of quartz sand and ranges 0.2–0.46 mm (fine to coarse sand). In addition, a medium height wave exposure results in intermediate morphology states with reduced to moderate supratidal areas and high intertidal profiles as the most common configuration. Some reflective profiles can be also seen in the less exposed locations.

2.2. Videometry

All the beaches were monitored using the infrastructure of the Gipuzkoa videometry network. This network uses the coastal videometry technology KOSTASystem developed by AZTI. The camera calibration and orthorectification method is based on the study of Holland et al. (1997). It consists of a two-step calibration (intrinsic and extrinsic) and allows the orthorectification of the images on a uniform z plane or in a predefined digital terrain model grid.

Each station has a specific number of Gigabit Ethernet cameras and fixed lenses, depending on the point of view and the dimensions of the beach. A camera supervision algorithm was set up to regulate the daily functioning interval, the cycle frequency and length, as well as the cycle window in which every element of the station is powered on (cameras, router, and switch). For the capture and processing of the images SIRENA software is used (Nieto et al., 2010). SIRENA creates 4 types of images from each camera: snap (instantaneous images), timex (average images), var (variance images) and timestack images (defined profile images). In previous applications, the cycle duration was set to 10 or 20 min, every 1 h, and the capturing frequency was 1 or 2 Hz.

In the present study, from June 15 to September 15, the configuration of the coastal stations was optimized to update the information visualized in the app to every 30 min, with a survey time of 08:00 to 18:00 UTC. Since the power system in most cases is photovoltaic, the update frequency is limited by the consumption associated with the image capture, processing, and the transmission cycles.

2.3. Beach user density (BUD) estimation

The beach user density (BUD) is defined as the percentage of the number of pixels that have been classified as occupied (beach users or belongings associated to users) from all the pixels analysed in the predefined region (ROI).

\[ BUD = \frac{\text{Number of pixel classified as occupied}}{\text{Total number of pixel analysed}} \]  

(1)

For this purpose, a new detection algorithm (Hondartzta) was developed (see details in Appendix A). Implementing an algorithm that automatically performs beach occupation estimation is a complex task, mainly due to the difficulty of processing outdoor images that are subjected to changing light and weather conditions. To overcome this drawback, a three-step method was followed:

1) Use of pixel imaging descriptors that are robust to illumination changes such as texture descriptors.
2) Use of a weak classifier to allow feature redundancy to generate a probabilistic map.
3) Employ a level-set over the probabilistic map to accurately remove spurious detections and regularize the estimated segmentation.

Fig. 2 shows an example of the detection algorithm results in the beach of Santiago-Zumaia.

2.4. Beach attendance (BA) estimation

The estimation of the total number of people on the beach (BA) is also a relevant value for coastal managers to manage and plan the use of the beach. It is related to the total number of people on the beach and it is obtained from the following formula:

\[ BA = BUD \times S \times k \]  

(2)

where $S$ is the available beach surface ($m^2$), and $k$ is the estimation of the number of individuals per square meter occupied. The $S$ parameter varies according to the tide level in the study site. Therefore, three regions of interest (ROI) are set up, considering the representative tide level (high tide, mid tide, and low tide), and avoiding processing non-sandy areas. To calculate the available surface of the beach, the ROI used for the detection is rectified at the mean level of the supratidal beach. At each time of image capturing, the algorithm matches the tidal level with the corresponding ROI (Fig. 3).

2.5. Beach carrying capacity (BCC) and beach access management under COVID-19

The beach carrying capacity parameter (BCC) is defined as the maximum beach occupation percentage allowed, based on the recommendations of the beach capacity ratio of $c = 8 \, m^2/person$, established by the Gipuzkoa Provincial Council in the COVID-19 context, and on the calibration parameter $k$ (number of individuals per square meter occupied):

\[ BCC = \frac{1}{kc} \]  

(3)

If the real time BUD estimated from the detection algorithm is larger than the BCC, then the recommendation is not respected. Therefore, it was defined an occupancy threshold (BUD/BCC) that indicates the level of beach occupation ranging from 0 (low occupancy/empty beach) to 1 (full capacity/recommendation not respected). For this purpose, a text
information and a colour-based display were implemented in the app (Table 1). The green and yellow values indicate that the COVID-19 recommendations ($8 \text{ m}^2/\text{person}$) are respected.

The information obtained from the system was then processed to be accessible to authorities, local managers (local councils and police and users. The results were displayed via a web/mobile app (Nik Hondartzak) for real time information, and special warnings were sent to managers via emails alerting of occupancy evolution or maximum capacity reached. For this purpose, an information exchange structure was set up in which video image captures were deposited with their configuration files and with the data to be displayed. An implementation was developed to execute the occupation algorithm at predefined intervals and to generate the text information (beach occupation information) and the cropped images (showing only the region of interest) that will be visualized in the app. A summary of the methodology developed here is summarized in Fig. 4.

In addition, to avoid erroneous beach access management produced by inaccurate beach user detections (caused by cloudy conditions or building produced shadows), an extra app was developed to allow managers to manually control the beach occupation status displayed for each beach. Moreover, during the summer 2020 the data were continuously analysed in collaboration with authorities and coastal managers to reconsider the beach capacity ratio of $8 \text{ m}^2/\text{person}$ initially set.

The developments of the Nik Hondartzak mobile/web app were opensource, multiplatform and based, among other technologies, on HTML, JS, JAVA and SQL, so the connectivity between our system and third-party systems was optimal. The platform consisted of some basic modules/functionality which could be adapted and expanded with other functionalities upon request. Personalization and user experience design were essential for the app. These are the functions included in the app: (1) Real time location, (2) Personalization of the application to the corporate image, (3) Real-time data, (4) Content manager to manage the beaches, (5) Push notifications, (6) 4 languages included, (7) Publish on Google play and (8) Publish in App store. The app also included information about the hourly tide levels and subaerial and intertidal surface evolution forecasted daily for each beach (Fig. 5).

### 3. Results

#### 3.1. Number of individuals per square meter occupied ($k$)

The $k$ parameter was computed from images and data obtained

---

**Table 1**

| BUD/BCC       | Colour display | Text information    |
|---------------|----------------|---------------------|
| BUD/BCC $\geq 1$ | Red            | Full capacity       |
| $0.6 < \text{BUD/BCC} \leq 1$ | Yellow         | High occupancy     |
| $0.3 < \text{BUD/BCC} \leq 0.6$ | Green          | Medium occupancy   |
| BUD/BCC $\leq 0.3$ | Green          | Low occupancy      |
during previous years at Bakio beach and 8 other beaches of the Basque Coast. Bakio’s beach was chosen as the main test site due to the amount of data available and the existence of manual counting records together with images from the videometry station.

During summer 2013, the BUD data obtained by means of videometry was compared with the data obtained by manual counting. The manual counting methodology was carried out every day at 10:00 and 16:00 (UTC) during the summer season (from June 1 to September 30). The video images were analysed at the same time as the manual counting were performed. To obtain the BUD parameter, only the subaerial beach was analysed, and bathers were not considered, assuming that they had some subaerial beach area occupied with a bag or bath towel that would be detected by the algorithm.

Fig. 6 shows the correlation between BUD (obtained from image analysis) and BA/S. BA/S was obtained by dividing the result of manual counting between the subaerial beach area.

During summer 2014, a validation campaign was carried out at 8 beaches of the Basque Coast. For that, BA derived from manual counting was contrasted against BUD from photos taken at the same time, in four sunny days along the summer. Fig. 7 shows the relation between BUD and BA/S in all these beaches. S is the subaerial beach area for each case.

In both cases the relation between BUD and BA/S is close to 0.3 with an $R^2 > 0.93$. Thus, there is a clear evidence that in the most common beach typologies and attendance levels of the Basque coast, the $k$ ratio (persons/m²) is around 0.3.

### 3.2. Beach carrying capacity (BCC)

The beach carrying capacity parameter ($BCC = 1/kc$) is seen as the maximum BUD allowed based on the recommendations of social distance in the COVID-19 context.

This, with a $k = 0.3$ and a $c = 8 \text{ m}^2$ per person, leads to a theoretical limit beach carrying capacity of around 0.4 ($BCC = 0.4$). During the implementation of the methodology there were a series of meetings with the local authorities of the different councils to review this parameter.
Some asked a more restricted limit of 10 m²/person, which leads to a BCC of 0.33. From a common agreement, it was decided to start the summer season with a BCC of 0.35. Later during the summer, this BCC limit was modified in the range between 0.3 and 0.4 depending on the feedback received from each local council.

It must be pointed out that, as shown from the results from previous years, values between 0.3 and 0.4 were usually reached only during the more crowded days (e.g. Bakio never exceeded 0.35 during summer 2013). Values over 0.4 were only observed in some special cases usually related with very populated beaches that are drastically reduced during high tide.

With these results, we have shown that 8 m² per person, is a good balance between applying social distancing measures, without being too restrictive with the access to the beach.

3.3. Image live processing success rate

Fig. 8 shows the success rate (%) obtained at each station during the summer 2020 service. The success rate represents the relative number of images that were captured, transferred, processed, and successfully shown in the mobile app. In general, the system operated effectively, with a success rate of more than 70% in all the beaches. 8 (Saturraran, Santiago-Deba, Itzurun, Malkorbe, Zarautz, Antilla, Ondarreta and La Concha) of the 14 beaches had a success rate of over 90%. 4 (Ondarbelts, Gaztetape, Zurriola and Hondarribia) had a percentage between 80 and 90% and only one station (Santiago-Zumaia) had a success below 80%.

The reasons of failure were related to three different factors: i) hardware failures (loss of internal CPU’s clock configuration, which affected the image capture and transmission), ii) unstable mobile communications (delayed image delivery to the database, which affected the image processing in time) and, iii) software problems (system crash).

3.4. Beach user density (BUD)

The occupancy classification based on the BUD/BCC ratio is shown in Fig. 9. Red, yellow and green colours correspond to full occupancy, high occupancy and medium-low occupancy, respectively.

As a general rule, all the analysed beaches had a medium-low occupancy during more than 70% of the time. Some beaches (Saturraran, Ondarbelts, Malkorbe - zone 2, and Hondarribia - zone 1) never reached the full occupancy level during the summer despite the great number of beach users registered this year because of their large subaerial beach areas.

The beaches with full occupancy level, and closed, less than 5% of the time (Santiago-Deba, Itzurun, Santiago-Zumaia, Malkorbe - zone 1, Zarautz - zone 3, Antilla, Ondarreta and Hondarribia - zone 2) correspond to beaches with high occupancy associated with relatively limited but systematically present subaerial beach.

Management was the most problematic in Zarautz and La Concha beaches where the beach entry was restricted to beach users between 5% and 10% of the time. In the case of Zarautz, the zones 1 and 2 (highly urbanized zones) presented higher access restriction levels in comparison to zone 3 (natural dune zone). Zarautz and La Concha both had a high user attendance and are long beaches, with a small subaerial beach during high tide.

Gaztetape has similar occupancy levels (full occupancy larger than 5% of the time) but has a different configuration. It is a very small beach, with little beach attendance and with almost no supratidal beach during high tide. There, the closure of the beach was related to the absence of the supratidal beach.

3.5. Comparison with pre-COVID19 era

A comparison between data analysed during 2020 and data collected during 2019 has been performed. For this purpose, the data were first normalized to allow a correct comparison. Data collected during 2019 were post processed applying the same BCC/BUD thresholds as in 2020. Since some videometry stations were not active in 2019, the comparison was done for 8 of the 14 stations.

The first issue that stands out is the high number of days classified as high-occupancy or full-occupancy in summer 2020 compared with summer 2019 (Table 2). In 2020, 6 beaches (Antilla, Zarautz, Malkorbe, Santiago-Zumaia, Itzurun, Santiago-Deba) registered more than 20 days of high occupancy, and Hondarribia and Saturraran registered 15 and 12 days of high occupancy, respectively. This corresponds to more than twice the number of days of high occupancy recorded during 2019, in almost all the beaches. In addition, all the beaches that, in 2019, reached full occupancy conditions increased this number in 2020. Zarautz and Itzurun are especially noteworthy, with 20 and 10 days of full occupancy in 2020, respectively, in contrast to 4 and 0 days in 2019.

In Fig. 10, morning and afternoon attendance during 2019 and 2020 is calculated for each summer month in 3 of the beaches with high attendance values. In general, beach attendance is between 2 and 3 times higher in 2020 than in 2019. This might be related with the larger number of sunny days and higher temperatures registered during summer 2020. Based on the monthly weather reports published by the Basque meteorological agency (Euskalmet), both the summer of 2019 and 2020 were hot and dry in the coast of Gipuzkoa. For example, in July...
2019 there were 8 rainy days (>1 mm) compared to 7 in July 2020, both below the average. On the contrary, in August 2019 there were 9 rainy days in contrast to 10 in 2020, both around the average values for the month. Sunstroke was normal or slightly high in both years except for July 2020 which was exceptionally high with 20%–30% higher than average. Summer temperatures in 2019 and 2020 were high (1 Celsius degree above the average temperature) comparing to the 1981–2010 reference period, with several extreme temperature events. Nevertheless, the weather during summer of 2020 was good in terms of beach use, and except for a greater insolation in July 2020, the rest of the parameters were similar in both cases.

This reveals a high demand of beach activity by the population in the context of COVID-19, as other recreational activities have been drastically reduced and beaches are seen by the users as safe spaces where social distancing can be applied.

Beach attendance temporal distribution variations were also observed. Previously to 2020, a bimodal distribution in the daily attendance patterns were commonly observed (Informe depara Dipu, 2019), with one peak in the morning (around 11:00 UTC) and a second and in some cases higher peak in the afternoon (around 16:00 UTC), revealing a clear trend for people to attend some beaches mostly in the afternoon.

In terms of spatial distribution, behavioural changes were observed in 2020, in comparison to the pre-COVID-19 years. Beach areas that in the past year were low affluence areas (usually areas far from the shoreline, where temperatures can be very high), have been occupied in 2020. That is, the spatial distribution of beach users observed in previous years, where there was a higher concentration of people near the shore (non-uniform distribution), has been shifted to a uniform spatial distribution (users uniformly spaced along the beach). An example of this change in the behaviour of beach users is shown in Fig. 11, for two high attendance days (2020 vs. 2019) in Antilla beach. This behaviour demonstrates that people have complied with the recommendations of the Gipuzkoa Provincial Council, respecting the social distance.

### 3.6. Use of the Nik Hondartzak app

The Nik Hondartzak app was downloaded to more than 50,000 devices throughout the 2020 summer season. 65% of the downloads took place during the second half of June, at the beginning of the season. In July and August, 30% and 5% of the downloads were registered, respectively. 64% of downloads were made to mobile devices (52% android and 12% iOS) and 36% have consulted the web app.

The images uploaded to the app are exempt from the Spanish Data Protection and Digital Rights Guarantee Act (LOPDGDD) 2018, as no person can be identified due to the resolution available.

Fig. 12, shows the usage of the app by day of the week for the period June 15 - September 15, 2020. The app is mostly used on weekends (Saturday and Sunday) and the maximum use occurs on Sundays (26%). On working days, the usage percentage is between 10 and 13%, with no large difference between them. Surprisingly on Fridays, being the day closest to the weekend, the percentage drops to 8%.

If the consultations are disaggregated by hour of the day (see Fig. 13), it is noted that most consultations take place in the afternoon. App users do not consult the app much early in the morning and the maximum number of consultations occur between 16:00 and 17:00 (UTC). The number of consultations remains high until 19:00 (UTC).

In addition, all the app consultations were geo-located (Fig. 14). This information is of great interest for beach managers as it gives an idea of the provenance and preferences of beach users without doing extensive polls.
It is noticed that most of the consultations were made from locations along the coast of Gipuzkoa (blue square) and from the three nearby largest cities (red stars). Since two of the nearby cities, are not on the coast, people consulted the state of the beaches before traveling to visit them or during the journey to the coast (note the number of enquiries made along the motorway connecting these two nearby capitals with the Gipuzkoa coast). Also, some app enquiries were made from Madrid and Barcelona (most populated cities in Spain) and from other coastal regions along Spain like Galicia, Cadiz, and Tarragona. It is also interesting to note that these last regions are typical touristic destinations for the people living in the Basque Country.

4. Conclusions

In the context of COVID-19, a methodology for the management of the beach carrying capacity by means of coastal videometry has been developed and applied to the coast of Gipuzkoa. It aimed at ensuring the necessary social distance recommended by authorities and resulted in providing real time beach occupation information through a web/mobile app to coastal managers and beach users.

To this end, a beach user detection algorithm based on a machine learning approach has been developed allowing to perform automatic assessment of beach attendance in real time at regional scale. The coastal videometry network of Gipuzkoa, based on KOSTASystem technology, covers 14 beaches, with 12 stations, along 50 km of coastline. For each beach, a simple classification of occupancy (low, medium, high, and full) was estimated as a function of (1) the beach user density (BUD) obtained in real time from the images, and (2) the maximum beach carrying capacity (BCC), defined based on the recommendations of social distancing in the COVID-19 context. This result was displayed in real time via the app, as well as the last image of the beach, and an hourly forecast of the available dry and wet beach areas for the day.

During summer 2020 (June 15 - September 15), beaches showed a
medium-low occupancy in more than 70% of the days (survey time 08:00–18:00 UTC). Some beaches never reached the full occupancy level, and the most problematic beaches had a full occupancy levels between 5- to 10% of the time. From continuous interactions with the authorities, changes in the maximum beach carrying capacity have been tested in these beaches. It has been shown that the maximum beach capacity ratio of 8 m²/person established initially by the authorities, was a good balance between applying social distancing measures, without being too restrictive with the access to the beach, and that this ratio can be recommended in the future for similar situations.

The app showed a strong and favorable reception from beach users (more than 50,000 downloads), which is similar to the maximum daily beach attendance of the 14 beaches of Gipuzkoa altogether. In addition, the large number of consults performed in the nearby largest non-coastal cities allows to consider that the application contributed to the reduction of unwanted displacements and of beach crowding in a conscientious way.

A comparison of the results of 2020 with the pre-COVID-19 era have shown some remarkable patterns in beach users’ behaviour. Although the weather during the summer season was similar in 2019 and 2020, the level of beach attendance was 2–3 times higher in 2020. This reveals a high demand of beach activity by the population in the context of COVID-19 as local tourism has been promoted. Other recreational activities have been drastically reduced and beaches are seen by the users as safe spaces where social distancing can be applied.

Furthermore, changes in the spatial and temporal distribution have been observed. In contrast to previous years, in 2020, the subaerial beach was occupied in its full extension and, for similar attendance ratios, higher and more regular spacing between individuals was observed. Moreover, in 2020, the beach attendance was spread throughout the day, in contrast to the previous year that showed a peak of attendance later in the morning and, a stronger peak in the afternoon. This confirms that beach users have been concerned about keeping social distancing measures.

This work has shown that providing real time information of beach occupation to beach users and beach managers can help in the short-term/daily beach management. Unquestionably, monitoring in real time the affluence of each beach improves managers criteria to open/close the access to the beach. In addition, having this information available greatly facilitates communication between managers and users.

In the longer term, the analysis of this information provides the necessary data for beach carrying capacity management and can help the authorities in controlling and determining the maximum capacity of beaches for future situation. Moreover, if the COVID-19 distancing recommendations change in the future, the present method can easily be accommodated. Coastal videometry with a performant detection algorithm is a powerful tool to provide such information at regional scale and the method presented here is applicable to other sites with different morphodynamic characteristics and different tidal regimes.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence
the work reported in this paper.

Acknowledgments

This work has been supported by the Gipuzkoa Provincial Council, the Zarautz Council, and the Donostia-San Sebastian Council. The authors would like to acknowledge the technical assistance and data provided by the Bizkaia Provincial Council. Roland Garnier acknowledges funding from the Provincial Council of Gipuzkoa through the Fellows Gipuzkoa Programme (Ref: 2020-FELL-000007-01).

APPENDIX A. The hondartza detection algorithm

A.1. Algorithm formulation

To generate illumination robust descriptors, the filter bank defined by Leung and Malik (2001) was considered. The Leung-Malik features were designed for texture recognition and segmentation. They consist on the responses of the image patches to a set of 48 linear filters, among which there are 36 elongated filters at varying orientations, scales and phases, together with 8 center-surrounding difference of Gaussian filters, and 4 low-pass Gaussian filters.

These filters (Fig. A1) are capable of mapping different textural and colour information from the image and, in fact, convolutional neural networks (Liu et al., 2019) automatically learn Leung and Malik similar filters on their low-level layers as image descriptors. To obtain the high-level description of the image each Leung and Malik filter is convolved over the three CIELab channels (Martin et al., 2004; Johannes et al., 2017) of the image.

After computing the features for every image in the training set, the following goal is to separate the feature space, finding boundaries that split it in two partitions that classify well unseen examples. Many well-established techniques for supervised learning exist in the literature, including logistic regression (Hastie et al., 2009), neural networks (Egmont-Petersen et al., 2002) or support vector machines (SVMs) (Vapnik, 1998). In this work our statistical classifier is trained by means of the Boosting methodology. Boosting, and AdaBoost in particular (Freund and Schapire, 1997), are a class of algorithms that combine a set of very simple (weak) classifiers, to build a stronger ensemble classifier. This algorithm acts on a training set \((x_1, y_1), \ldots, (x_m, y_m)\), where each \(x_i\) is in the domain \(X\) and each \(y_i\) is in the label set \(Y = \{-1, 1\}\). At initialization stage, a simple linear classifier \(h_1\) is assigned to each label, with equal weights, \(D_1(i) = 1/m\). In each iteration of the algorithm, the weights are modified so that the weight of misclassified examples are increased, leading the classifier to focus on the worst classified examples, increasing this way performance. Final classifier is found as a weighted sum of the best weak classifier found at each iteration, as:

\[
H_{final}(x) = \text{sign} \left( \sum_{t} a_t h_t(x) \right)
\]  

(A.1)

After initialization, the structure of the algorithm is:

1. Finding the best weak classifier in this iteration, \(h_t\), when importance of examples is weighted by distribution \(D_t\).
2. For that best classifier, computing error rate \(e_t\) as:
\[ e_t = \sum_{i=1}^{m} D_t(x_i) \cdot \Pr(h_t(x_i) \neq y_i) \]  \hspace{1cm} (A.2)

where, since the weak classifier \( h_t \) is better than random, then. \( e_t \leq 1/2 \)

(3) Computing the corresponding weight \( \alpha_t \) with which \( h_t \) will contribute to the final classifier \( H_{end} \), as:

\[ \alpha_t = \log \left( \frac{1 - e_t}{e_t} \right) \]  \hspace{1cm} (A.3)

Here, as \( e_t < 1/2 \), then \( \alpha_t > 0 \). Also, the smallest is the error \( e_t \), the largest is the factor \( \alpha_t \), assigning more importance to the weak classifier \( h_t \) in \( H_{end} \).

(4) Building a new weight distribution \( D_{t+1} \) based on \( D_t \). For each example \( i \):

\[ D_{t+1}(i) = D_t(i) \cdot \exp(\alpha_t \Pr(h_t(x_i) \neq y_i)) \]  \hspace{1cm} (A.4)

so the weight of misclassified examples is increased for the next iteration, in which the corresponding weak classifier will be selected as the one that better handles harder examples. Renormalizing the weight distribution \( D_{t+1} \), so that it sums up to 1.

At the end of the iterative procedure, the designed strong classifier can discard redundant features, and effectively classify each pixel as belonging to one class and the other in less than 1 s. The classifier output corresponds to a probabilistic map of values in the \([0,1]\) range where the higher the value, the more posterior probability of the pixel of belonging to a occupied region and the closer to 0, more probability for belonging to an unoccupied beach region. These values are thresholded by a predefined value calculated over the training set to maximize the balanced accuracy. Results are depicted in Fig. A2.

![Fig. A2.](image)

(a) Detail of the segmentation performed by the Ada-boost classifier, (b) Detail of the final result of the segmentation after applying the level set based regularization (c) Detail of the initial level (coarse segmentation initialization) set function (d) Detail of the final level set function.

At the end of the iterative procedure, the designed strong classifier can discard redundant features, and effectively classify each pixel as belonging to one class and the other in a reasonable amount of time. The model is then passed on to the part of the software dedicated to prediction so that, based on the knowledge included in the model, it is possible to apply exactly the same calculation of statistical descriptors in a new image. Depending on the responses of the pixels in this image and comparing them with the responses of the training images, Hondartz software is capable of efficiently classifying the pixels as corresponding to person or beach. However, a reduced amount of information provided by a relatively small training set of images leads to the misclassification of some pixels.

However, the classifier segmentation produces coarse segmentation that reduces the overall accuracy of the system. Because of that, the initial probability map provided by the classifier is regularized by a level-set based active contour approach as described in: \cite{bereciartua2015,bereciartua2016}.
A.2. Algorithm performance

The system was trained on a first beach (Beach 1) and evaluated against four other beaches (Beach 2–4) to quantify performance metrics. Firstly, the performance of three different classification algorithms was evaluated: logistic regression (Hastie et al., 2009), support vector machines (SVMs) (Vapnik, 1998) or the proposed AdaBoost (Freund and Schapire, 1997).

| Beach   | Accuracy | AdaBoost | SVM | Quad. Regression |
|---------|----------|----------|-----|------------------|
| Beach 1 | 94.869   | 93.359   | 92.331 |
| Beach 2 | 97.517   | 95.417   | 94.357 |
| Beach 3 | 96.429   | 94.555   | 87.607 |
| Beach 4 | 96.804   | 94.874   | 94.679 |
| Beach 5 | 89.835   | 88.688   | 83.043 |

Table A1

From such a moderately sized training set, coarse segmentations could be generated, which the level set implementation of the active contours was able to refine to achieve good performance. A comparison of the performance (in terms of balanced accuracy, i.e., percentage of well-classified pixels) of the proposed methodology, for AdaBoost and two other state-of-the-art classification methods is reported in Table A1. AdaBoost outperforms SVM and quadratic regression as a tool for finding an initial coarse segmentation.

To analyse the effect of the level-set based regularization, the result of the level set segmentation shown in Fig. A2 (a, b) is inspected. Therein, the initial segmentation, obtained with the supervised classification process is able to locate the areas of the image that contain people, but introduces noise, in the form of a complicated contour. The active contours refinement performed in the same image effectively removes this noisy output, by iteratively simplifying the contour of the segmentation, while attaching to the borders of the located structures. Moreover Fig. A2 (c, d) shows how the ability of the level set implementation to change the topology of the implicit function that embeds the segmentation contributes to the removal of outliers and wrongly classified pixels. For a quantitative analysis, the performance of our system in a small set of images of beach scenes was checked. Images belonged to four other different beaches, and were taken at varying times, implying changes in illumination, and different occupancy rates.

From such a moderately sized training set from beach 1 coarse segmentations could be generated, which the level set implementation of the active contours was able to refine to achieve better performance on different beaches not included on the training sets (Fig. A3).

Fig. A3. Comparative results (balanced accuracy BAC). Blue) Proposed method with the level-set based regularization, red) Proposed method without level-set regularization.

References

Balouin, Y., Rey-Valette, H., Picand, P.A., 2014. Automatic assessment and analysis of beach attendance using video images at the Lido of Sète beach, France. Ocean Coast Manag. 102, 114–122.
Bereciartua, A., Picon, A., Galdran, A., Iriondo, P., 2015. Automatic 3D model-based method for liver segmentation in MRI based on active contours and total variation minimization. Biomed. Signal Process Contr. 20, 71–77.
Bereciartua, A., Picon, A., Galdran, A., Iriondo, P., 2016. 3D active surfaces for liver segmentation in multisequence MRI images. Comput. Methods Progr. Biomed. 132, 149–160.
Caselles, V., Catté, F., Coll, T., Dibos, F., 1993. A geometric model for active contours in image processing. Numer. Math. 66 (1), 1–31.
Cisneros, M.A.H., Sarmiento, N.V.R., Delrieux, C.A., Piccolo, M.C., Perillo, G.M., 2016. Beach carrying capacity assessment through image processing tools for coastal management. Ocean Coast Manag. 130, 138–147.
Da Silva, C.P., 2002. Beach carrying capacity assessment: how important is it? J. Coast Res. (36), 190–197.

Diputación Foral de Gipuzkoa, 2020. Memoria valorada para la adecuación de la playa de Zarautza en cuanto a movilidad y estancia con distanciamiento social por COVID-19. Gipuzkoako Foru Aldundia/Diputación Foral de Gipuzkoa.

Dwight, R.H., Brinks, M., Sharavanskumar, G., Semenza, J., 2007. Beach attendance and bathing rates for Southern California beaches. Ocean Coast Manag. 50, 847–858.

Egmont-Petersen, M., de Ridder, D., Handels, H., 2002. Image processing with neural networks—a review. Pattern Recogn. 35 (10), 2279–2301.

Eusko Jaurlaritza/Gobierno Vasco, 2020. Estrategia de Turismo Vasco 2030. Plan de Marketing del Turismo Vasco 2017-2020. Eusko Jaurlaritza/Gobierno Vasco.

Freund, Y., Schapire, R.E., 1997. A decision-theoretic generalization of on-line learning and an application to boosting. J. Comput. Syst. Sci. 55 (1), 119–139.

González, M., Uriarte, A., Fontán, A., Mader, J., Gyselaers, P., 2004. Marine dynamics. Oceanography and marine environment of the Basque Country 70, 133–157.

Guillén, J., García-Olivares, A., Ojeda, E., Osorio, A., Chic, O., González, R., 2008. Long-term quantification of beach users using video monitoring. J. Coast Res. 246, 1612-1619.

Gulden, F., 2018. Automatic quantification of beach occupation using oversegmentation and machine learning. In: Master Thesis Project. Shore Monitoring & Research.

Hastie, T., Tibshirani, R., Friedman, J., 2009. The Elements of Statistical Learning: Data Mining, Inference, and Prediction. Springer Science & Business Media.

Holland, K.T., Holman, R.A., Lippmann, T.C., Stanley, J., Plant, N., 1997. Practical use of video imagery in nearshore oceanographic field studies. IEEE J. Ocean. Eng. 22 (1), 81–92.

Hoobnout, B.M., Radermacher, M., Baart, F., Van der Maaten, L.J.P., 2015. An automated method for semantic classification of regions in coastal images. Coast Eng. 105, 1–12.

Informe de AZTI para Diputación Foral de Gipuzkoa, 2019. Análisis mediante videometría de la ocupación de la playa de Antilla, durante la temporada estival de 2019.

Jiménez, J.A., Osorio, A., Marino-Tapia, I., Davidson, M., Medina, R., Kroon, A., Archetti, R., Ciavola, P., Aarnikhof, S.G.J., 2007. Beach recreation planning using video-derived coastal state indicators. Coast Eng. 54, 507–521.

Johannes, A., Picon, A., Álvarez-Gila, A., Echazarra, J., Rodriguez-Vaamonde, S., Navajas, A.D., Ortiz-Barredo, A., 2017. Automatic plant disease diagnosis using mobile capture devices, applied on a wheat use case. Comput. Electron. Agric. 138, 200–209.

Kammler, M., Schernewski, G., 2004. Spatial and temporal analysis of beach tourism using webcam and aerial photographs. Coastline Reports 2, 121–128.

King, P., McGregor, A., 2012. Who’s counting: an analysis of beach attendance estimates and methodologies in southern California. Ocean Coast Manag. 58, 17–25.

Leung, T., Malik, J., 2001. Representing and recognizing the visual appearance of materials using three-dimensional textons. Int. J. Comput. Vis. 43 (1), 29–44.

Liu, L., Chen, J., Fieguth, P., Zhao, G., Chellappa, R., Pietikäinen, M., 2019. From BoW to CNN: two decades of texture representation for texture classification. Int. J. Comput. Vis. 127 (1), 74–109.

Manning, R.E., Lawson, S.R., 2002. Carrying capacity as “informed judgment”: the values of science and the science of values. Environ. Manag. 30, 157–168.

Martin, D.R., Fowlkes, C.C., Malik, J., 2004. Learning to detect natural image boundaries using local brightness, color, and texture cues. IEEE Trans. Pattern Anal. Mach. Intell. 26 (5), 530-549.

Nieto, M.A., Garau, B., Balle, S., Simarro, G., Zarruk, G.A., Ortiá, A., Tintoret, J., Álvarez-Ellacuría, A., Gómez-Pujol, L., Orfila, A., 2010. An open source, low cost video-based coastal monitoring system. Earth Surf. Process. Landforms 35 (14), 1712–1719.

Pak, A., Adegboyé, O.A., Adekunle, A.I., Rahman, K.M., McBryde, E.S., Eizen, D.P., 2020. Economic consequences of the COVID-19 outbreak: the need for epidemic preparedness. Frontiers in public health 8, 241.

Vapnik, V.N., 1998. Statistical Learning Theory. Wiley-Interscience. New York.