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GAVIN: a new platform for enriching 3D virtual indoor navigation with social-based geotags

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Abstract—Social Networks, geotags, and Virtual Reality (VR) are parts of the everyday life of most of the people in the world. In particular, geotags represents a way to discover places through metadata added to media. At the same time, VR reproduces with high accuracy real places that we can navigate through a browser or a 3D visor. In this paper, we present GAVIN to fill the gap between social media geotagging and Virtual Indoor Navigation. GAVIN is a platform for the navigation of virtual environments able to exploit BIM Digital Twins and geolocated data coming from different sources and, in particular, from the social experience bounded to a real/virtual place. In the paper we provide design and implementation details on the GAVIN platform, and we present some performance evaluations.

Index Terms—geotagging, VR, BIM, Digital Twins, virtual navigation, indoor navigation, coding.

I. INTRODUCTION

In recent years, the massive usage of social networks like Facebook, Twitter, Flickr has changed the way people use to interact with each other and with the environment. Social networks allow you to discover new places allowing users to add geographical metadata to various media (i.e. geotagging data) and linking social posts related to these places. However, social networks collect information and subjective evaluations of places, but can not allows people to experience staying there. This problem is much more evident in the navigation of indoor environments. Indeed, for outdoor areas, geolocalized maps enriched with 3D visualizations tools are available on the web [1] [2]. On the contrary, it is hard to access and visualise indoor environments. This limit can be overcome using Virtual Reality (VR). VR is applied in many contexts like gaming, industries (particularly I4.0), and tourism. This technology is in general used to discover and explore places reproduced into a virtual environment using a 3D engine. Moreover, for creating a virtual environment on the concept of Digital Twins, that is the real-time digital counterpart of a physical object or process, consolidated Building Information Modelling (BIM) techniques can be usefully adopted. Indeed, integrating an existing BIM model and VR solutions allow defining an interactive tool through which it is possible to have a virtual overview of the status and information associated with a real environment [3] [4]. The choice of BIM technology compared to classic CAD allows us to have an immersive environment enriched with geometric and management information. This paper aims to import geotagging opportunities (e.g., the ones used in social networks) into Digital Twins implemented using

consolidated BIM and VR technologies. This will offer a new way for people to personalising and sharing the experience of visiting or living a place. In particular, we present GAVIN (Geotagged, Accurate, Virtual Indoor Navigation), a solution for integrating geotagging with imported BIM models and VR technologies, and for providing new functionalities to discover the physical world through virtual navigation. To achieve this goal, GAVIN implements different tools in a single platform. First of all, it includes a geohashing hierarchy and three-dimensional code based on the Open Location Code Algorithm to refer to a resource in the world. The provided approach is innovative because allows geotagging areas of different sizes (depending on the length of the geocodes). As the second step, in GAVIN we designed and developed a back-end platform able to enrich BIMs with different kinds of geotags, such as: internal geotags created by the user of the BIM instance; external geotags retrieved by external social systems (e.g., Twitter and Flickr); IoT geotags, which are the data generated by IoT devices installed in the referred area. Finally, GAVIN enables the reproduction of the enriched BIM for personalised virtual navigation inside your browser, smartphone, or 3D visor. GAVIN uses the 3D Unity Engine to make the users' BIM navigation interactive. Inside the Unity Engine, it retrieves the geotags stored in the back-end platform to show additional information and objects at the tagged position.

The remainder of the paper is organized as follows. The state of the art is analyzed in Section II. Our motivations coming from the state of the art analysis are discussed in Section III. The design of the platform architecture is discussed in Section IV. The real implementation of the platform, with particular focusing on the enabling technologies and their cooperation, is discussed in Section V. Experiments performed on the advanced geotagging platform prototype to get metrics are discussed in Section VI. Conclusion and future works are summarised in Section VII.

II. STATE OF THE ART

The unexpected and fast impact of Social Networks on society has meant that this new phenomenon has become a real source of Big Data, easily interrogable, interacting, and constantly evolving. Compared to other data sources, Social Data is localized. The localization content has been exploited by several works, especially for marketing scopes. In this field, in [5] the authors used geolocalized media contents

downloaded from Flickr and Panoramio to understand which are the most important point of interest (POI) in a city. Similar work has been proposed by the authors of [6]. They try to discover the POI in a city and which ones are POI only for foreign visitors; again, they use geolocalized posts on Twitter and Flickr from visitors to understand what is valuable and what it is not. These works exploits information from people's data, but they consider only a part of the entire existing data.

As explained by [7] data from social network sources such as Twitter, Flickr, and so on are more similar to outliers than average data, this occurs because only a part of the overall source data is localized. This thesis is in part justified by [8]. In this work, the authors try to understand who enables the geolocalization services in Twitter and the demographic differences between who do and who do not do that. They concluded that the difference between people is age, political country-related rules, which affects the real data balance. As seen in literature, there is an evident and growing mistrust in geotags consider a reliable source of data useful for understanding human aspects. For this reason, many recent studies are moving to change only how these data are shown, contextualizing them in maps, videos, virtual or augmented realities. In this way, data are shown to the users according to policies of appropriate and straightforward localization. In [9], the authors used a simple 2D map as a base to show tweets localized in relative areas. Also, in [10] is proposed Social Street View, a solution for geodata visualisation on their geographical context. In particular, a Street View map is enriched with Instagram, and Twitter geotags. In this work, it was possible to join the concept of map exploration and tag exploration, but without immersive results. In [11] the authors proposed Geollery, the most advanced combination of geotagging and trendy map exploration of social networks. The authors can build the entire real environments such as cities, parks, and so on by using real maps and allows the users to navigate in VR the 3D virtual reconstruction. In this work the reconstruction of the virtual places is not faithful, and indoor navigation is impossible.

Moreover, in [12] the authors proposed an innovative solution for augmented reality, using geolocalized videos and a public cartographic infrastructure similar to Google Maps, offered by the Korean government, but the immersion and user experience is not optimized. To define an accurate representation of the real environment and buildings, and at the same time to integrate it with geotags, an optimal solution can be using BIM models. Building Information Model/Modelling (BIM) has been widely applied in architecture, construction, and management. Having an interactive virtual environment turns out to be a challenge that has been extensively reviewed in the literature. In [13] is presented a method for the virtualization of existing buildings that allows converting a building acquired by laser scanning into a 3D model on a BIM platform. In particular, this instrument can get the point of cloud used to create a 3D model based on a mesh. Moreover is possible to obtain a BIM model from a point cloud opportunely processed. Furthermore, the BIM model is

combined with the latest virtualization experiences to develop semi-immersive applications in Augmented Reality (AR). In [14] the digital content is overlapped to the geometrical model to define an interaction with real physical space. The VR technology can be combined at the same time with the Geographic Information System (GIS) and BIM to solve the problems in the construction of sponge city [15]. With BIM, it is possible to detect the design (construction) problems and large-area management and reduce the construction costs improving efficiency. Starting from a preliminary analysis on BIM technology and its integration with VR, we can identify different innovative applications. In [16] the authors summarize the Post Occupancy Evaluation (POE) method studies to provide a detailed framework that can integrate the collected data and 3D spatial information, and at the same time define user-friendly functions and provide tests and data visualization tools. In our work, we want to put together the concept analyzed so far in order to propose a tool, that through the innovation of geotags and BIM models, allows navigating an enriched virtual reality in order to give the users the possibility to have an immersive experience.

III. MOTIVATION

Our work is focused on the opportunities of using geotags to explore the world. Geotags have a great potential that can be exploited in different applications, such as for tourism and smart cities [6] [10]. Thus, it is important to provide users with flexible tools to use geotags to share information but also personal comments and experiences related to a place. In literature, as discussed in Section II, there are different solutions to push geotags in 2D maps, giving to the user the possibility to move within a virtual map of the world retrieving geotags in the area of interest. However, to the best of our knowledge, geotag-based Indoor Navigation is not well investigated in the literature, even if it can really change the way people can experience museums, public offices, hotels, airports, and any type of building. In our view, a challenging approach to support Indoor Navigation is exploiting VR with geotag visualization. This means matching each virtual environment with geo-localized information of real components that add knowledge to the virtual navigation. In literature, there are some works that address the integration of BIM models in VR environments [11]. A BIM model is used as a Digital Twin of a building and integrates into a VR scene static information, such as the building position and geometry, the size of a door, and so on. Such localized pieces of information are pre-loaded in the BIM and remain unchanged during the time. Furthermore, BIM gives us the possibility to have a realistic virtual reproduction of a building compared to CAD technologies. In our work, we want to extend such types of imported BIM models with dynamic data that comes from the authoritative geo-referenced database and also from subjective geotagged data repositories such as social networks. And for that, we designed and developed GAVIN. GAVIN is a platform able to fill the gap between social media geotagging and virtual Indoor Navigation, by configuring the navigation of

virtual environments with dynamic contents that can evolve during the time according to the social experience bounded to a real/virtual place. In this way, the discovery of new locations can be socially driven and, at the same time, the enrichment process related to a location is always running and can better respond to the current needs of people. To achieve these challenging results, GAVIN has to implement the following functionalities:

- 1) creating a self trusted geotag database;
- 2) exploiting the digital buildings twins as geotag source;
- 3) create a geotagged indoor navigation system.

In the next sections, we present the reference architecture of GAVIN, identifying the key functional components, and details on the current implementation of the framework.

IV. GAVIN DESIGN

The GAVIN platform has to recognize people and location, collect, store, and exposes geotag using the structure defined. Moreover, with the integration of automated systems like IoT devices and sensors it is possible to create a particular kind of geotagging, and finally, to collect the in-house data through the proposed API-based platform. The overall components of our platform are showed in Fig. 1, where we can see:

- 1) a Backend Layer that implements all the necessary functionalities in terms of BIM model, virtualization, and geolocation building;
- 2) a Data Layer where storing internal, external and IoT geotags and BIM models;
- 3) an API Layer to expose both data and GAVIN functionalities to external services or applications;
- 4) an Application Level to allowing users to interact with the platform.
- 5) an Identity Manager (IDM) layer to recognise users and check for service access.

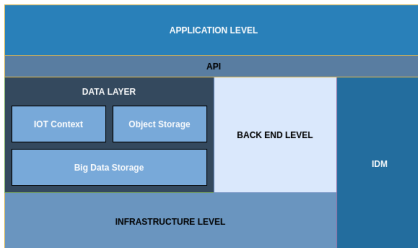


Fig. 1: Platform Components

The data layer in the left part of Fig. 1 consists of the Object Storage, Big Data Storage, and Context Data.

Object Storage stores immutable data that are read and written in entire blocks like BIM models. The Context Data data stores the IoT devices' live status and these data are kept up to date directly from the devices. The Big Data storage component stores the data that can be queried by the GAVIN platform, which are the geotags and the history data coming from the Context Data component (after they have been refined).

The interaction between users and the platform takes place in the highest layers of Fig. 1, on the Application Layer, built over the API layer to exploit all the GAVIN functionalities. The Application Layer is composed of the final client applications that can use GAVIN, and they are browsers, smartphones, and 3D visors with the relative native apps.

Finally, users start to use GAVIN with one of the provided applications they prefer. Inside the application, users can authenticate themselves using the IDM component, and then they can access the data through the application itself, which is able to use imported BIM models, to fetch and produce data on the Data Layer and finally to simulate the navigation.

V. IMPLEMENTATION

In this section we present the implementation of the GAVIN platform, starting from the description of the key architectural components as shown in Fig. 1 and presenting the main services that the platform has to provide.

A. Back-end Layer

1) *Building Design and Virtualization*: BIM is an holistic process based on digital transformation in Architecture, Engineering, and Construction (AEC) industry. The BIM model innovation consists of the digital information's interconnection in open and protected data. Through the interconnected information is possible to create a realistic virtual 3D model of the buildings, with a data-set, and data visualization function that gives the possibility to define the environment's real-time analysis. Thanks to BIM, it is possible to structure the data in order to create a virtual replica of a building and connect it with sensors or Geotags. In particular, by the use of tools such as Revit by Autodesk, Unity Engine, and properly designed scripts is possible to navigate an existing building enriched with various information associated with Geotags.

2) *Building modelling using BIM*: The BIM model is created with the Autodesk Revit software. We used the Unity game engine to set up the virtual environment. To import the BIM on Unity is necessary to export the FBX (filmbox) file in order to have all the functionalities of the original Revit file. With this format is possible to create interoperability between 3D applications and the 3D BIM model. Through Unity, we can directly import the .fbx file exported from Revit, but in this way, we have a model without materials and textures. To solve this problem, and to import the textures of the 3D model created in Revit, it is necessary to use the third software. In our work, we have chosen to use the Simlab Composer software to integrate all the textures to the .fbx model to be imported into Unity. Moreover, in the import process can be some problems with the integration of all 3D BIM models' parameter in Unity, and for this reason, is important to define a backend infrastructure that gives us the possibility to set some property in an automatic way through REST API protocols. In order to enable the users to view the virtual environment and to interact with information obtained by geotags, we implemented some scripts that execute the simulation.

3) *Building Geolocalization*: The main characteristics of geocoding depend on the algorithm used to implement the localization and the related representation. One of the most popular geolocation algorithms is Open Location Code, developed by Google, which produces Plus Codes [17]. One of the main limits of Plus Codes is that they don't localize altitude and to overcome this limitation we propose our own three-dimensional geocoding algorithm called Extended Plus Code (EPS). EPS is designed starting from the Open Location Code algorithm, which is based on the WGS84 standard. Plus codes are generated following a Discrete Global Grid (DGG) and the output codes use an alphabet of 20 digits composed of numbers and letters. Valid Plus Codes are for example 8F9PH2X8+X4, 8F9PH2X8^10 and, 76HM538X+X7C. We can just concatenate Plus codes with the altitude value, expressed as height above the sea level, using a proper separator (^). Finally, to avoid too long codes, we can constrain length to one digit for an integral part, and one digit for the decimal part. We can call this algorithm and relative geocodes EPS. The following strings are valid EPS geocodes 8F9PH2X8+X4^999.9, 8F9PH2X8^10 and 76HM538X+X7C^0.

To apply geotags in virtual navigation we need to have a georeferenced building, to localize the building model in the World it is necessary to match the coordinates of the building model (local coordinates) in the virtual environment and in the real one (global coordinates). It is possible to convert the global X, Y coordinates by using equirectangular projection and aligning the Real World axis and the Virtual World axis using a transformation matrix as explained in [18].

B. Data Layer

The starting model of the Data Layer is shown in the left part of Fig. 2, and it is composed of the Object Storage, Big Data, and Context Components:

a) *The Object Storage*: is used to store BIM models for virtual navigation. Minio is the micro service-based Object Storage included in the Kubernetes Architecture;

b) *The Big Data Component*: must store the entire set of geotag data arriving within the platform. The designed database should also include historical data from the IoT infrastructure installed in the building. In order to have high performance, scalability, and availability on the Cloud infrastructure we use the MongoDB database. This database is able to store GeoJSON data and to make geo-query on them;

c) *The Context Storage*: contains the context, (i.e the status) of a trusted IoT infrastructure. Our reference architecture is described in [19]. In this paper, the author exploits the Orion Context Broker as data storage and message Broker and NGSI as data protocol for the IoT devices, both developed by the Fiware Foundation and released with open source license. Orion Context Broker, in particular, is a publish-subscribe data broker, based on a self-managed MongoDB instance, from which exploits the geo query capabilities which are exposed from the rich Rest API library of Orion;

C. IDM Layer

As shown in our architecture depicted in Fig. 1, we need an Identification Manager to authenticate and authorize users and relative actions inside the platform. To this end, we use the IDM Keyrock by FIWARE [20]. The interaction between IDM and the backend is based on the Rest APIs provided by Keyrock itself (see Fig. 2).

D. API Layer

The backend level is organised as a REST interfaced microservice, which main features are listed below.

- F.1** Authentication and Authorization user system based on Keyrock IDM by Fiware;
- F.2** data querying on the Data Layer components using the official drivers;
- F.3** data mining from external sources already used in the State of Art, like Twitter and Flickr APIs;

A special mention goes to the *Explore* and *Discovery* functions exposed by the backend.

a) *The explore query*: is a simple function that given a EPS and eventual filters on the geotag fields, it returns all the geotags posted in the given EPS, matching the eventual filters;

b) *The discovery query*: exploits the geoquery functionalities that MongoDB offers. The function receives a given EPS and it finds all the *inner* areas (in EPS code) that contains at least one geotag that matches the eventual filters, these results can be used following in a *explore* call function.

E. Application Layer

Unity is the Engine we use to virtualize the environments and to navigate them interacting also with the API layer for retrieving the geotags. Unity allows also the deployment of different native apps. We exploit this feature to develop only one time the Application level and to deploy them on different devices. In particular we built an Android App, a 3D Visor app built specifically for the Oculus, and finally a browser-based app based on the WebGL technology. All of these application allows exploiting the GAVIN platform at all.

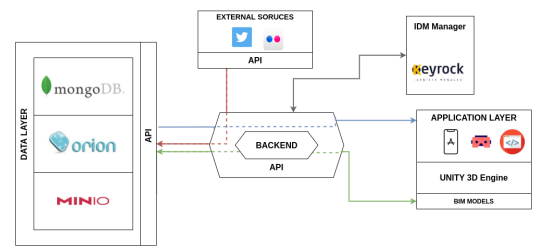


Fig. 2: Backend Implementation

F. First demo of GAVIN

We show a screenshot of our first demo of the GAVIN platform in Fig. 3 based on the browser application. In the demo, we see in foreground the building we are navigating, at the bottom left we keep a box showing the EPS code,

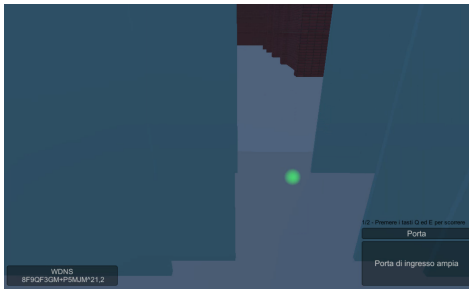


Fig. 3: Demo Gavin in browser app

which specifies where we are at this moment in the simulation, instead in the low right edge showing the geotags in the current EPS.

VI. PERFORMANCE EVALUATION

We evaluated the system using the browser GAVIN app. In particular, we tried to understand the delay during the virtual navigation, to fetch the data through the *explore* and the *discovery* functions, already described before. We deployed the GAVIN platform inside a single virtual machine with a 3.1 GHz quad-core x86_64 IntelXeon E3-12 CPU and 8 GB RAM. The client app has been run inside a workstation with 4 × Intel Xeon E-2124G CPU @ 3.40GHz and 32.2 GiB of RAM.

We analyzed the GAVIN performance considering varying the dimension of the input dataset in the data layer (100.000, 500.000, 1.000.000 geotags) and the dimension of the returned geotags in a single API call (500, 5000, 50.000 geotags). The performance value we are interested in is the Time To Respond Value (TTR), which informs us about the time elapsed from the moment when we send a request to the server to the moment we receive the response.

A. Explore Function Performance

The explore function allows getting all the geotags posted in a given area identified by an input EPS.

In Fig. 4 we are using histograms to compare the average TTR varying the required geotags in a single function call (colours in histograms), considering the different overall input data sizes. On the histogram plot, we see also three lines, each line represents the behaviour of the TTR considering the same body size and different data input. This test is very interesting because shows that changing the input dataset does not affect the performances (lines have a slope near to zero), instead of increasing the response dataset increases the system stress (bars on histograms are higher if the response is bigger). In the first case, we have a great database scaling, in the second case we have a data transmission transfer rate that is not optimal.

We make some consideration about:

1) *Database Scaling*: Database Scaling is the characteristic that allows us to understand how the input dataset size affects the TTR value. The slope for all three lines in Figure 4 is near zero, and this happens because the TTR is not correlated to the input dataset size. This result can be achieved thanks to the

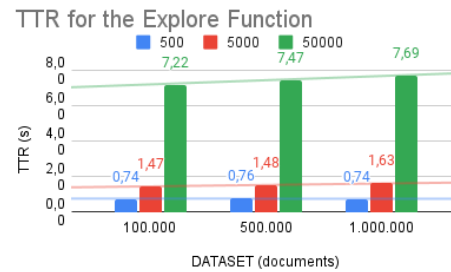


Fig. 4: Explore function performance

MongoDB indexing on the data filter field that allows to not *query* all the data to fetch the correct ones. Thus MongoDB does not require checking the entire dataset, because it already knows where to find data matching the provided filters.

2) Lot Calls With Few Data vs Few Calls with Big Data:

We have the possibility to define the number of the returned geotags in a single function call, and as we see in the Fig. 4, this affects TTR performance a lot. In particular, we can move to two different policies:

- 1) Send lot of calls to the explore function requiring small dataset;
- 2) Send few calls to the explore function requiring a large dataset.

Which policy must be applied depends on the behaviour of the system when we increase the required data size. In Fig. 4, considering for example the dataset composed of 1.000.000 of data, we see that a linear increase in the body size produces a sublinear TTR time increasing. Consider the body size of 500 geotags as a reference value that requires 0,74 seconds to be completed. To get 5.000 geotags we should do 10 function calls, the expected time will be equal to 7,4 seconds. Sending a single function call with 5.000 geotags requires instead only 1,54 seconds. Same for 50.000 geotags, that should require 100 function calls with an expected time of 74,0 seconds that is much greater than 7,67 seconds that is the time required to get in a single function call all the 50.000 data. Given these results of course is better to require more data and send fewer function calls.

B. Discover Function Performance

The discover function acts a bit differently with respect to the Explore function. As we already explained, it starts from an input area to find the tagged subareas. The datasets we used to test the performances are the same for the explore function, thus we will use three different datasets containing 100.000, 500.000 and 1.000.000 geotags. The Fig. 5 shows the TTR of the discover function varying the input dataset. As we can see, we have lower performance compared to the explore function. In fact, the lightest configuration with the smallest dataset is completed in an average time of 2.8 seconds, almost two times the time required to complete the explore function with 5.000 geotags. The heaviest query, instead, requires around 24 seconds that is three times the time required to run the

explore function with 50.000 geotags. Also, the increasing factor is higher with respect to the explore function, as we see comparing the growth of the TTR curve with the dataset size. When we increase the dataset size by 100 times, we have a TTR that is around 10 times the TTR, highlighting a clear linear behaviour.

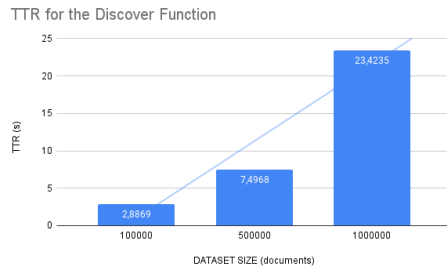


Fig. 5: Discover function performance

Fig. 6 depicts the discover function performance, where the CPU saturation velocity is evident. In the plot we see that with the smallest dataset the micro service is already quite stressed, with a CPU usage near to 75%, it reaches about 90% with the bigger dataset, and it reaches 100% of usage with the biggest dataset.

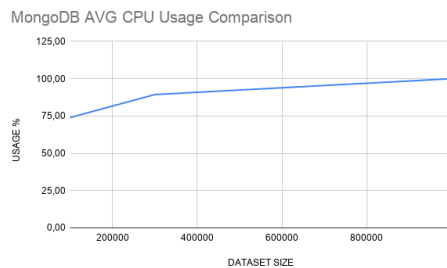


Fig. 6: MongoDB CPU usage during Discovery execution

VII. CONCLUSION AND FUTURE WORKS

This paper presents a new indoor and social navigation platform called GAVIN. With GAVIN, we extended the actual concept of geotagging for dynamic indoor navigation, using our EPS geocode algorithm able to identify any area in the world with the desired precision, thus giving the users the possibility of resizing the indoor are they are interested to navigate. In the future, we aim to use the GAVIN platform together with Augmented Reality, for a more attractive interaction with users.

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