Spatial-Temporal Visualization Tool for Hospital Support for Infection Spread and Outbreaks

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Abstract: Hospital-acquired infections (HAIs) are a major concern today, especially when related to multidrug-resistant bacteria, as they are associated with increases in healthcare costs, prolonged length of stay, and attributable mortality. Tracking the presence of these infections requires interweaving spatial-temporal information from patients and microbiological laboratory results. However, this is normally a manual process and the big amounts of daily clinical data makes it error-prone and time-consuming. In these processes, the temporal dimension is usually taken into account, but not the topology and spatial distribution of patients within a hospital building. Interactive Information Visualization can be used to bring together information from various data sources and to make these spatial-temporal relationships understandable to the human eye. We propose a new interactive visual tool for the exploration of infection spreads within hospitals. The tool presents several connected views to help analyze the epidemic situation of a hospital over time and understand the information contained in the epidemiological indicators.

1 INTRODUCTION

Multidrug-resistant microorganisms are a growing challenge for public health since their treatment is a complex process. These types of microorganisms have also a high impact on hospital-acquired infections (HAIs) (Cassini et al., 2019), as infections caused by these pathogens are associated with increases in healthcare costs, prolonged length of stay and attributable mortality (Serra-Burriel et al., 2020). In a healthcare setting, pathogens can be transmitted from contact with an infected patient, a healthcare worker, or a contaminated environment (Monegro et al., 2023). Tracking the presence of these infections requires interweaving spatial-temporal information about the patients and microbiological laboratory results. However, the large amounts of clinical data that are captured daily pose some challenges and make the process error-prone and time-consuming to clinicians in the task of combining this information to make any inference, and to hospital administrators in their decision-making processes (Caban and Gotz, 2015).

The development of interactive Information Visualization can help overcome this information overload (Rind et al., 2010) and discover new knowledge, such as patterns in the clustering of the pathogen and the transmission among patients. However, current approaches tend to study diseases at the population level in geographic areas, rather than local spatial-temporal studies at the building level.

We introduce a new interactive visual tool for the exploration of infection spreads inside hospitals. The tool presents several connected views to help analyze the epidemic situation of a hospital through time and understand the information contained in epidemiological indicators. In this paper, we describe the tasks and requirements defined with experts in epidemiology and hospital management, and we present the views developed to perform these tasks as well as the interactions between them and with the user.

2 RELATED WORK

The development of visualization tools for epidemiologists and policy-makers has focused mainly on

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the task of disease surveillance over a population. In these developments, the spatial-temporal information of a disease normally describes the evolution and spread at the population level for a post-analysis of what happened usually in a geographic area (Chorianopoulos and Talvis, 2016; Sakai et al., 2004; Su et al., 2021). However, despite the increasing acknowledgment of the importance of tracing people for the study of the spread of infections in recent years, very little has been done on the analysis of contacts and spread of diseases at the individual level and taking into account the spatial characteristics of the building they are in over time (Oppermann and Munzner, 2020), especially in hospital environments.

Regarding the representation of the spatial topology and data in buildings, Opperman and Munzner (Oppermann and Munzner, 2020) presented a set of visual decision-support tools centered around occupancy data for management and planning in buildings. However, their goal is to visualize non-trajectory spatial-temporal data relating to large-scale indoor environments. Another example is the one presented by König et al. (König et al., 2021), which is an interactive visualization system that uses a 3D representation of building interiors for a unified sensor data display (e.g. temperature or humidity).

Regarding the development of visual analytics for contact tracing and epidemiological studies, Baumgartl et al. (Baumgartl et al., 2021) presented a visual analytics approach to support the analysis and reconstruction of transmission pathways, patient contacts, and the progression of an outbreak at the patient level. They designed multiple specialized views and highlighted their adaptation of the storyline visualization for contact tracing. Their views include an epidemic curve, a contact network, a timeline, and a storyline-like view. Müller et al. (Müller et al., 2020) applied an RNN model for the detection of potential infections, transmissions, and infection factors, and they proposed a visual interface to explore the model results. Sondag et al. (Sondag et al., 2022) presented a visual analytics approach for the inspection of infection maps in an evolving emergency response situation. They introduce the concept of representative trees to visualize a time-varying infection map of disease spread, and interactive visualization techniques for the assessment of different control policies.

3 METHODS

3.1 Data

To carry out the study of the spread of a disease and the presence of infectious outbreaks in hospitalized patients, it is necessary to intertwine microbiological reports with the spatial and temporal localization of patients. This consists of a complex and time-consuming process that is not usually found in real open datasets, both due to the challenge of recording it and the privacy problems it can involve.

To assess the tool, we study the spread of the *Clostridioides Difficile* (CD) pathogen in a hospital setting. The CD is the main cause of infectious diarrhea in hospitalized patients, with increasing rates of mortality, incidence, and hospitalizations (Hota et al., 2012). The choice of the best method for its treatment continues to be a topic of debate today, while its incidence increases, reaching values of 92 per 100,000 inhabitants in North America and Europe (Lital Meyer et al., 2014).

To represent the transmission of this pathogen at a high level of detail, we use a realistic generated dataset of patients with their information (i.e. demographic data, length of stay, admission day, and information about their treatment, among others). In each moment, these patients are in a bed of a service (this service can be a Ward, the ICU, the ER, a Radiology Room or an Operating room) and have a state of health. This state takes its values from the SEIRD (Susceptible, Exposed, Infected, Recovered, Dead) epidemiological model (Brauer, 2008), which we adapted to the infection we are dealing with. In this case, we included the NS (non-susceptible) state for those that have immunity, and the possibility of being already colonized in newly admitted patients. We generated this dataset with a simulation model, that combines an agent-based model with an adaptation of the SEIRD epidemiological model(Kim et al., 2023).

In our simulation, time is discrete, divided into *steps* or periods. During each step, patients can move from one room to another, their states of health can change, and places can be infected or decontaminated. Steps are tuned to 8 hours, representing usual work shifts. For each step, information about the patients and places is saved: whether there are newly admitted or discharged patients, what movements took place, which places were contaminated or cleaned, and in what state of health each patient is. For further details, we refer the reader to (Kim et al., 2023).

3.2 User Tasks

With the help of epidemiologists, we have defined a series of tasks that they need to perform in order to detect when and where the infection transmissions take place and how infectious outbreaks originate. To be able to understand the final action that experts must carry out to complete each task, we applied the framework defined by Munzner (Munzner, 2009), which is useful for describing the reason why each visualization is necessary, thus it helps differ between the many goals the tool will have. With this framework, we transformed the description of each task from a domain-specific language to a more abstract form, thus we could see similarities and differences between them. In this way, we avoid redundancies and overlapped tasks. The resulting tasks are presented below, an example of this process is presented in T1:

T1. *Analysis of the situation of the infection in diverse places in the hospital over time.* To identify and compare the epidemic state of the hospital between different places and over time using several epidemiological indicators, which were discussed and chosen with the experts. These are mortality rate, incidence, incidence density, period prevalence, and point prevalence (e.g. when are there more deceased? Which service presents more incidence?). Application of Munzner's framework:

- High level of abstraction: to discover new information and generate or verify a hypothesis.
- Mid level of abstraction: to locate cases in the hospital, the targets are known, but not the locations.
- Low level of abstraction: to summarize cases and show an overview of all possible targets.

T2. *Detection of sources of infection in a period of time.* To discover when and where the first concentrations of cases occurred, this is, to locate the focal point of the infection.

T3. *Detection of sources of infection in a point of time.* To trace and identify when and where the first case of infection occurred and how the spread took place from there by locating the first patient that appears infected.

T4. *Study of potential outbreaks.* To discover whether or not an outbreak occurred in those concentrations of cases. The definition of infectious outbreak depends on the pathogen that is being studied: in the case of the CD, an outbreak is defined as three or more epidemiologically linked cases within a period of seven days or fewer (West Virginia Bureau for Public Health, 2013).

3.3 Tools

We developed the visual tool in the game engine Unity 3D with C#. This allowed us to create a 3D representation of a hospital and to show from different perspectives the topology and the interactions between patients at a low level of abstraction, which would ease the tracing of the disease. We modeled the different parts of the hospital and beds with Blender, and we used PostgreSQL for data persistence. This way, we could study diverse scenarios and make several tests by running the simulator and saving the newly generated datasets in a database automatically.

4 PROPOSED DESIGN

Based on the defined tasks, we present an interactive visual tool that has three main views (Figure 1): the Hospital view, which shows information about the spread of the disease in a spatial and temporal plane; the Epi view, which shows temporal information regarding calculated epidemiological indicators; and the Tabular view, which shows the values of said epidemiological indicators of the hospital in a tabular format sorted by location and time. Next, we are going to analyze each one in detail and, afterwards, to list the interactions that the user can perform with the visual tool.

4.1 Hospital View

The Hospital view shows the patients' movements at a low level of abstraction, as well as the evolution of the endemic situation of the places on a 3D representation of the hospital (Tasks 1-3). This view is composed of the visualization of the hospital and a toolbar, which allows the user to perform certain actions (Figure 1a). The 3D hospital allows to analyze the spatial distribution of patients at each moment, study where infected patients are located at an individual level, what contacts occur (i.e. when do they share a room), and where a greater number of patients are concentrated in different ranges of time.

Patients can be in one state of health at a time, which is color-coded: green represents susceptible patients, yellow exposed patients, red infected patients, purple recovered patients, black deceased patients, and blue non-susceptible patients. Through user-controlled animations, we can identify which

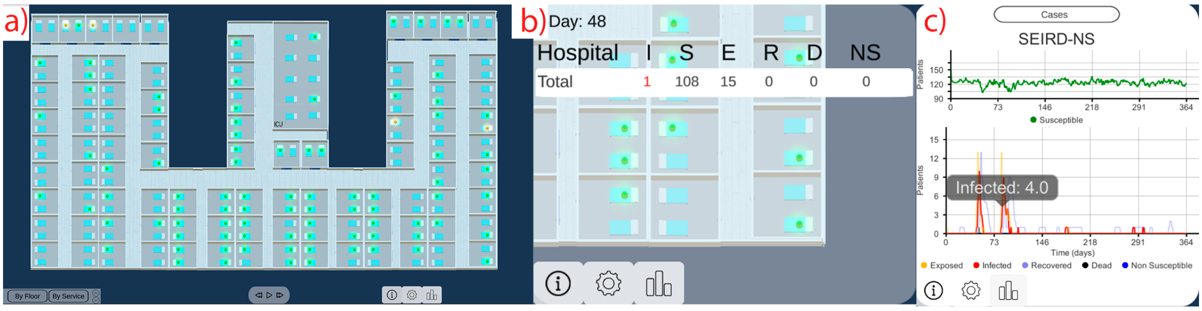

Figure 1: The interactive visual interface. (a) The Hospital view shows the spread of the disease in a 3D spatial-temporal representation. (b) The Tabular view shows the information of the other views in a tabular format. (c) The Epi view shows the epidemiological indicator selected by the user.

rooms and services the patients went to and how the infection evolved.

4.2 Epi View

The Epi view helps to study the evolution of the disease (Tasks 1, 4). In this view, the user can analyze several epidemiological indicators using line charts (Figure 1c): on the one hand, cases and point prevalence, that are displayed by day; on the other hand, incidence, period prevalence, mortality rate and incidence density, which are calculated by week. We present the cases in the SEIRD-NS format, which means, showing the number of patients in each state of health by day. Thus, it is possible to have a general view of the situation throughout the entire simulation, and then focus on a period of time by means of semantic zooming (Figure 2). Besides this, by hovering at each point we are able to see detailed information at each moment of time.

4.3 Tabular View

The Tabular view allows an analysis of the disease present in the hospital with daily aggregated information in space (Tasks 1, 2). In this view (Figure 3), the user can choose to see an epidemiological indicator (i.e. cases, mortality rate, incidence, incidence density, period prevalence, and point prevalence) calculated over the entire hospital or grouped by floor or service (Figure 3). In the case of the latter, the different services are color-coded in coordination with the Hospital view, thus making it easier to locate them on the map.

4.4 Interactions

In this section, we describe the interactions between the user and the tool, as well as between the visual components. The tasks that epidemiologists and hospital administrators have to carry out are complex in themselves, and searching for a case of infection in a hospital with 200 or more beds can be a long and consuming process. To assist in this work, we have applied a segmented color scale to easily identify the different states of health of each patient as indicated by Aigner et al. (Aigner et al., 2011). In this way, it is possible to see when transmissions happen – i.e. when a patient is red (infected) and a roommate turns yellow (exposed or incubating) –, and which patients might be future cases (those in yellow) that could support the spread. This also connects with the Epi view, in which we use the SEIRD-NS model obtained from the input data to represent the evolution of cases. In this model, we encode each state of health with the same color as in the Hospital view.

The Hospital view gives the user an overview of the space and allows them to interact with the camera by movements to go to one area or another, zoom in and out, or rotate to see from another angle. It is well known that the use of 3D representations can lead to problems of occlusion, perspective distortions, and shadows, among others (Munzner, 2015). In order to avoid these problems, we have implemented an orthographic camera, thus objects are rendered uniformly, without a sense of perspective.

In this view, the user can also perform other interactions, such as changing between the hospital floors to see one or another; advance, go back, pause, or resume the animation of the simulation; and advance or go back step by step in the simulation without the need for animation.

The user can also filter out the information that does not interest them at that moment (Shneiderman, 1996). This is possible by means of a toolbar, in which they can filter the patients by a range of age, gender, and state of health. The filtering is applied to the 3 views. Besides this, users can also perform zoom actions as defined by Shneiderman (Shneiderman, 1996) to focus on subsets of patients, by being able to distinguish patients' transitions between dif-

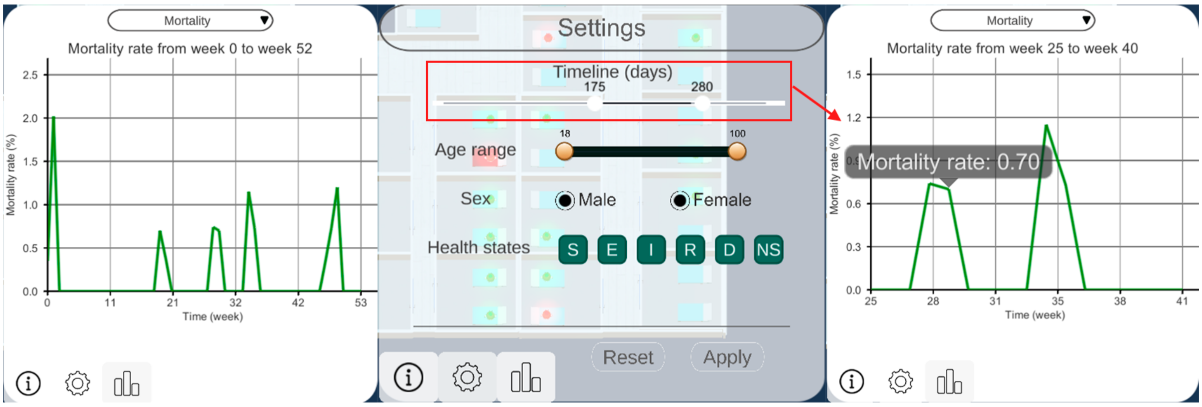

Figure 2: Semantic zooming process. At first, the user will see the epidemiological indicator for the whole period of time. Through a timeline, they can choose the range of time they want to study, and this will be applied to the Epi view.

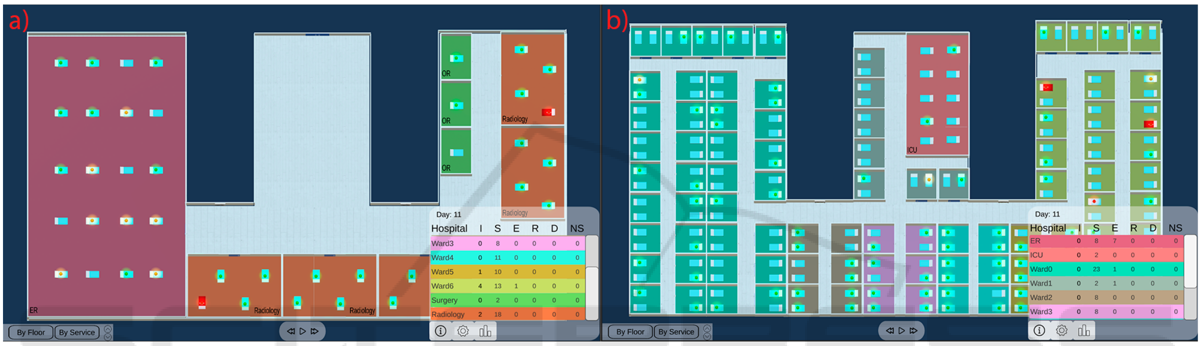

Figure 3: Tabular view shown with the Hospital view with several infected patients zooming by service. (a) First floor containing the remaining services (ER, Radiology and Surgery). (b) Second floor containing the Wards and the ICU.

ferent categories. This is done by highlighting information by floor or service to see changes in specific different areas (Figure 3).

5 DISCUSSION

We have developed an interactive visual tool for the analysis of the spread of a disease by multidrug-resistant bacteria, and the investigation of infectious outbreaks inside hospitals. This tool focuses on the spatial and temporal dimensions of the movements of hospitalized patients, as well as on the information provided by calculated epidemiological indicators.

When developing a medical visual tool, one of the main risks is the treatment of real clinical data. This can lead to problems regarding data quality, bias, or patient privacy, among others (WHO, 2023). By using realistic data generated with a simulation model (Kim et al., 2023), we have avoided these problems associated with handling sensitive and sometimes incomplete data. Through the use of synthetic data, we can know exactly where the patients were when their states of health changed. Regarding applying the tool to real data, there would be no differences between a simulated and a real environment in which the data was obtained with the same precision. Although we built the tool with simulated data, the current implementation provides the integration of data from log files and relational databases, allowing the integration from both simulated data and real health information systems.

The use of Unity for the development involved both advantages and limitations. Unity is a platform prepared for developing a 3D tool, so it offers a wide variety of libraries and great efficiency in its compilation time. However, it is not intended for data visualization, and so the asset store does not count with a great range of chart packages.

Furthermore, the scalability in the hospital modeling entails a challenge and a possible limitation of this tool. Nevertheless, we are working on an automatization of the creation of hospital floors with their rooms with beds in the necessary arrangements (i.e. orientation and position). The hospital presented in Figure 3 was created in this way.

This visual tool can have applications in health and in education: it can be used by epidemiologists and administrators in hospitals in their decision-making process (e.g. better admission control in the ER, more isolation of infected patients, or greater care in the movement of at-risk patients). It can also be applied, for example, in the Objective Structured Clinical Examination (OSCE), where the skills acquired by students upon completing their medical degree are evaluated. In these tests, they create simulated scenarios and students must make a series of decisions as doctors.

Our following step is to validate the visual tool by means of qualitative evaluations with specialized users to ensure its usability and usefulness.

6 CONCLUSIONS

In this paper, we propose a decision-support visual tool to help intertwine the spatial-temporal locations of hospitalized patients with information about their health conditions during the spread of an infection by multidrug-resistant bacteria. To do this, the tool combines several views which include a 3D visualization of a hospital, a 2D visualization of the temporal progression of the disease, and a tabular visualization to detail the information depicted in the other views. The interactivity of the created 3D model allows for a faithful representation of the movements and the infection processes, while the use of widespread charts can help understand the temporal progress through epidemiological indicators. The tasks were defined together with epidemiologists from hospitals from Murcia, and we consider that this tool is going to be of utility in different areas (infection control, decisions in a hospital, teaching). Our next step is to validate the usefulness and usability of the tool with said users.

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