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Immersive Analytics for Floods Management Semantic Trajectory Data Warehouse Ontology

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Abstract. Semantic Immersive Analytics is a new paradigm that has the capability for visualizing ontologies and meta-data including annotated web-documents, images, and digital media such as audio and video clips in a synthetic three-dimensional semi-immersive environment. More importantly, it supports visual semantic analytics, whereby an analyst can interactively investigate complex relationships between heterogeneous information and supports query processing and semantic association discovery. In our previous work we proposed a Semantic Trajectory Data Warehouse Ontology (STrDWO) [15], a tool supporting designers at the modeling of ontology-based trajectory data warehouses. In here, we intend to integrate our aforementioned tool with augmented Reality (AR) technologies to provide multi-sensory interfaces that support collaboration and allow users to immerse themselves in their data in a way that supports real-world geo-space analytics tasks. To do so, we present a Semantic trajectory data warehouse having an ontology-based multidimensional model. We illustrate our approach by a case study dealing with floods management.

Keywords: Data warehouse, trajectory data, ontology, floods management, immersive analytics, augmented reality

1 Introduction

The leapfrog of remote sensors and sensor networking technologies is leading to the eruption of disparate, dynamic, and geographically distributed mobility data. For a long while, location sensing devices such as (pda, smartphone, tablet) and sensor networks such as (WIFI, fiber optic,3G-4G networks) started becoming untethered. As a result, different structures of mobility data sources revealing the details of instantaneous behaviors conducted by mobile entities can be constructed.

Note that, trajectory data, which is a record set of gathered mobility data, can be associated to different domain-specific information. Trajectories are naturally represented as *raw trajectory* denoting a sequence of temporally-indexed positions. For example, a flood is defined as an overflow of water resulting from

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different bodies of water such as a river, a lake or an ocean. it moves with a varied speed and a depth that change instantly. Indeed, flood move in a geographical areas located near this river. In this case, we refer to flood waves as the moving object that moves in time and space and to flood movement as flood trajectories. In the other side, ontologies have emerged as more flexible, reusable and manageable modeling solutions. It may provide common model for different representations of flood trajectory data where designers can pick the appropriate knowledge to define flood trajectories in view of share, exchange or integration [15]. Alongside, data warehousing techniques are expected to analyze and extract valuable information from different flood trajectory data sources [14].

For this purpose, this paper throws light on a Semantic Trajectory Data Warehouse (STrDW). We emphasize a geometric module in order to represent common structures encountered in trajectories associated with links to application and geographic modules in order to maintain semantic interoperability. Furthermore, our model serves to define the STrDW conceptual model. Our proposal permits to save too much designers efforts and time needed to acquire domain knowledge since the latter is extracted from the floods ontology. This will mainly highlight the trajectory to be seen as a first class semantic concept, providing an ontology-based multidimensional model.

Immersive analytics represents a set of novel visualization techniques of big sets of data. The former investigates new display and interaction technologies for supporting analytical reasoning and decision making. Accordingly, we later use the aforementioned techniques to generate a STrDW for floods managements encompassing floods data from different data sources. And to facilitate data analysis and management we use immersive analytics technologies to introduce our vision of an AR tools for floods data visualization.

Therefore, this paper is organized as follows. First, we'll give an overview of STrDW modeling. Then we'll introduce the floods data ontology and the STrDW used for floods management. After that, we ll review previous works on immersive analytics. We'll introduce our vision of the future visualization system for our flood management STrDW. Finally, we'll conclude this work.

2 Semantic Trajectory Data Warehouse: Overview

Trajectory Data Warehouse (TrDW) is considered as an efficient tool for analyzing and extracting valuable information from heterogeneous trajectory data sources. A TrDW is the application of data warehousing techniques on trajectory data [13, 22]. Before getting to the TrDW, research communities were interested in analyzing spatio-temporal data in Spatio-Temporal Data Warehousing (STDW). There have been various proposals of multidimensional models for STDW [25] aiming at the integration of various data sources containing spatio-temporal data. Trajectory data is a particular case of spatio-temporal data characterizing objects mobility. Then, a TrDW is obviously a particular case of STDW where trajectory is the fact [13, 4]. However, obtaining an implementation of the DW is a complex task that often forces designers to ac-

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quire wide knowledge of the domain, thus requiring a high level of expertise and becoming it a prone-to-fail task. The first attempt to set a Semantic Spatio-temporal Data Warehouse is given by authors in [8] which annotate the datacube elements with domain ontologies as well as mathematical ontology. Data Warehousing works analyzed above present some limitations in the fact of managing trajectory data, especially when dealing with the semantic aspect of trajectory data. Several works in the literature consider the trajectory concept is beyond a record set of time stamped positions. Indeed, a trajectory exceeds its classical definition to be considered as a semantic entity related to a semantic layer of thematic information. So, the need to emphasis the trajectory to be seen as a first class concept motivated us to propose throughout this work a multidimensional model of TrDW, namely a Semantic Trajectory Data Warehouse (STrDW) model, which is meant to be more than a classical trajectory data repository for storing and querying raw mobility data. Recently ontology building attracted researches aimed at supporting TrDWs with semantic models [18, 14]. The multidimensional model presented by a STrDW conceptual model, inspired from an existing ontology model. This will emphasis the trajectory to be seen as a first class semantic concept, not only a spatio-temporal path. Thus, the semantic multidimensional model is meant to be more than a spatio-temporal data repository for storing raw mobility data. By exploring the literature, we find little concrete work on conceptual design of TDW considering the semantic aspect of trajectory data. Taking a brief overview on similar works, the closest and the only true design of TrDW using semantic concepts that can be recalled, is the solution discussed in [18]. In this paper, authors proposed an ontology-based TrDW related to the marine mammals field. The design methodology they propose deals with a specific domain ontology and a specific structure of trajectory data valid only for the case of marine mammals and didn't propose a generic methodology to extract the semantic TrDW model from a semantic representation of common structures of trajectories.

3 Floods Trajectory Data

A flood is defined as an overflow of water resulting from different bodies of water such as a river, a lake or an ocean. A flood therefore moves with a speed and a depth that change continuously. In addition, these movements generally affect the geographical areas located near this river or this lake or ocean with variable degrees. For this fact, we refer to flood waves as our moving object moving in time and space. We are looking through this topic to detect flood trajectories in real time in order to plan the paths of rescue agents to ensure the rescue task in optimal time. In this work, we'll opt for an ontological solution to model floods trajectories to help in their management, especially that ontologies really offer a great semantic richness (Figure 1).

We first identify the classes forming our ontological model. There is mainly the *Flood waves*, the highest node that inherits from the *Thing* class. Several other subclasses are related to the class *Flood waves* such as *Side, Flooded area,*

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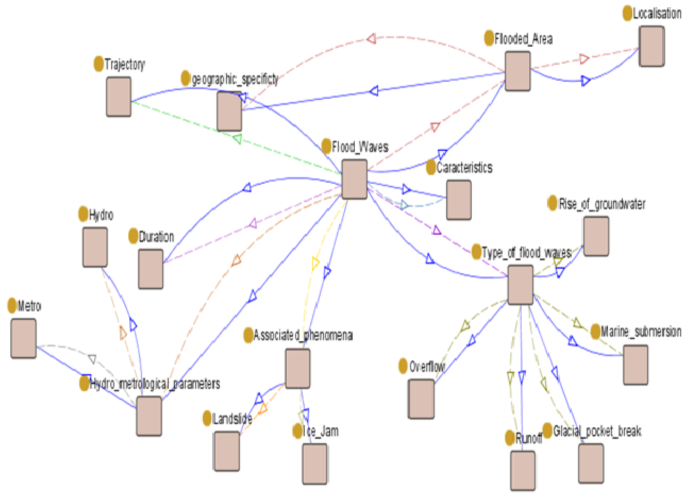

Fig. 1. Ontological modelisation of Flood wave

Time, Characteristics, Associated phenomenon, Hydro-metrological parameter, etc. Most of these subclasses themselves contain other subclasses for example: the subclass *Duration (Start date, End date)*, *Associated Phenomenon* subclass of *(Burrowing, Icebreaking, Icebreaking, Landslide, Gully)*, the subclass *Flooded Area (Geographic Specificity, Localization)*, the subclass *Type of Flood* itself includes other subclasses and sub-subclasses *(Overflow (Snowflood, Rainfall), Runoff (Rural Runoff, Urban Runof), Breakage of work (Dam, navigation channels, Reservoir, pumping station,etc), Marine submersion (Tsunami, Sea / Tide, and wave actions, ...)*. The subclass Type of floods will be detailed in the (Figure 2). Our model presents different types of interrelationships between classes, some of them are defined through our proposed model (Figure 3). We note for example:

- The *hasTrajectory* relation connects between *(Flood waves and Trajectory)*.
- The *is-a* relation connects between (*Flood waves* and *Type of flood waves*).

Later in the next section we'll integrate this model into a more general and generic model with more detail on trajectories and geographic specifications, the STrDW, to improve response time and emergency process in case of disasters.

4 Floods Management STrDWO

With the increasing use of ubiquitous localization and positioning technologies such as remote sensing, GPS and mobile technologies, huge amounts of data are

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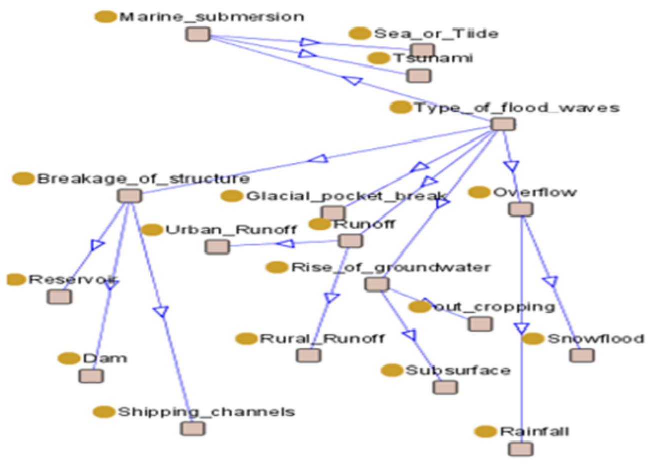

Fig. 2. Subclass modelling of Type of flood

being collected every moment. These location data are defined as the trajectory data. Typically, these types of data are in the form of a triple (x, y, t) where x and y form the geographic coordinates and t supports the moment when the moving object occupies that location [3]. Indeed, these voluminous data need to be stored according to the most appropriate model to ensure their best interpretations. For this fact, in this work ontology modeling is used for the proper representation of the floods management issue which encompasses big set of data. In this paper, we are interested in highlighting the STrDWO for floods management based on a work recently proposed by [14] and on the basic model initially developed by [24], consisting essentially of three ontologies (ontology of trajectories, a geographical ontology and a domain ontology). The model that we assume is made up of a generic ontology composed of four types of resources: fact, thematic, temporal and spatial are respectively represented in the following sub-ontologies modules :

- GTO: contains different concepts spatio-temporal necessaray for the geometric description of trajectory.
- FMO and GO:
  - FMO: describes domain ontology dedicated to represent the concepts necessary to understand the field of floods FMO: describes domain ontology dedicated to represent the concepts necessary to understand the field of floods
  - GO : specifies the geographical concepts related to undrestanding a trajectory.

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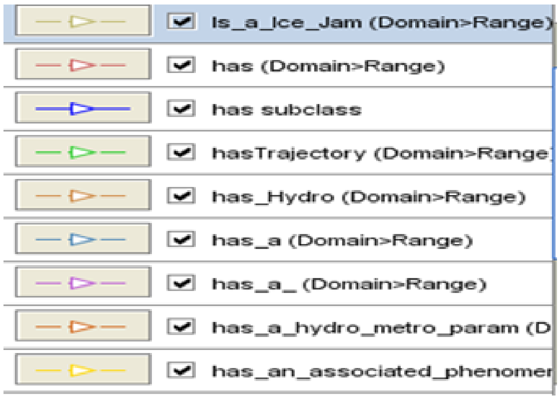

Fig. 3. Some types of relationship between the classes

- Temporal Ontology: Temporal concepts and roles are based on the standard Time-owl ontology3 developed by W3C.
- Spatial Ontology: Spatial concepts and roles are based on Geo ontology4developed likely by the W3C standard.

In addition, this model offers in parallel the different relationships and links connecting the different concepts. Among them, we quote (Figure 4):

- *hasAffected* is a property between the concepts Flood waves and Geographic Area means the area affected by this flood.
- *isLocatedIn* is a property between Flood waves and Trajectory describes the trajectory followed by the flood.
- *hasSpecificity* is a property between Trajectory and Geographic Area specified the trajectory specificity for each geographic area.

5 Immersive Analytics: State of The Art

Nowadays, with advances in immersive technologies used for interaction and display such as tangible screens and headsets they became widely used to analyze and explore data. In fact, such immersive environments support collaborative work for data exploration and leverage users' actions in such tasks. Also, the affordance of display devices used for analyzing data effects strongly the experience of user while interacting with these systems which effects, consequently, users' degree of productivity. Immersive Analytics (IA) is a new and emerging initiative defined by providing a set of techniques to augment human ability of making sense of noisy, massive, heterogeneous and multifaceted datasets and deriving insights from it based on high resolution and immersive environments. It is multidisciplinary research thrust representing an interaction of technologies for data analytics as it brings together researchers from visualization disciplines

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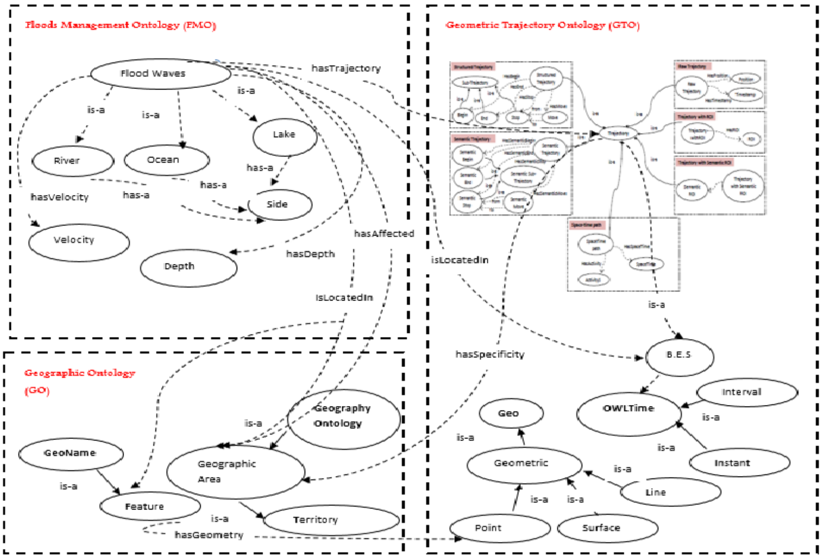

Fig. 4. STrDWO for floods management

in data science including visual analytics mainly, information visualization, scientific visualization, 3D natural user interfaces, hybrid, virtual and augmented reality. Visual analytics provides analytical reasoning facilitated by visual interactive interfaces [12]. IA, then, investigates how the emerging and powerful visualization, display and interaction technologies could be used for creating seamless data visual analytics and supporting analytical reasoning and decision making [5]. Since the rise of this research field, a lot of work has been done to visualize in immersive systems data coming from different applications and case studies such as: crisis management, animals tracking, medicine, etc [21, 11, 1, 7]. Actually, classical data visualization, despite its long history, has not gone much beyond tradition devices: keyboard, mouse, flat screen, etc. Which is not the case for IA as it supports data analytics in many ways by the usability and design of its user interfaces in such systems. For instance, immersive technologies permit to show many views at the same time. In fact, nowadays, rather than its complexity, data is considered as widely available. Such big datasets are difficult to precess. Indeed, decision making relies on computer processing of data. Otherwise, visual methods are advantageous for the exploration of large datasets, their understanding and then propitious decision making. In fact, big datasets need to be visualized in more than one view. IA allows people to organize views, make sense of data and reach collaborative conclusions based on a shared information space. Furthermore, it helps showing larger information spaces than desktop computers. Such interactions could allow movement within the views. Other works subdivided display space into multiple views, each presenting some aspect of the data. This requires to organize the visualized data within a single

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large view [12]. Emerging IA works focus on binding entities movement with data exploration process. For instance, in the work of [10] authors introduced a tool for data exploration based on the user location since Human Computer Interaction (HCI) relies on binding between user actions and system's response. This tool relies on mixed reality (MR) and virtual reality (VR) tracking techniques to detect their users movements and interact later with data exploration system. MR is the interaction between virtual and physical world. Hands movements are also detected and used to manipulated and select the data. Furthermore, in the work of [16] IA was applied to an animals tracking case study. I-Flight, a visual analysis system based on virtual reality for insect movement data is proposed. This system helps to understand flights movement and then its behavior in a simulated environment. I-Flight permits to visualize insects trajectories in their natural 3D geospatial context. In fact, such visualization system complements existing scientific methods and tools for analyzing and understanding data. Most of the work in the literature that visualized movement data used conventional desktop displays. From another side, immersion is beneficial in the acquisition of spatial knowledge. Also, virtual reality headset natively supports position tracking to allow users to move and look around naturally in the 3D environment. Differently, in other works IA was applied to environmental case studies. For example, researchers in [17] explored data recorded from approximately 18000 weather sensors placed across Japan in local and global contexts in a VR visualization system developed using the HTC Vive and the Unity engine. Originally, sensor data was visualized by the public via a simple web interface through a list of small maps with links for sensors. Accordingly, it was hard to get a global idea of the sensors at the national level, to respond to large scale natural disasters (floods, storms, etc). In this work authors went farther by investigating a variety of methods for user interaction with data: flying around the map, open an interactive window for any sensor, seek their position in time. Also, the VR provided a country-wide view of data and allowed querying of each sensor. To display the sensors in the 3D map of Japan, vertical bars are used, they change in height each time their value is updated to ensure a flexibility in data analysis and interpretation. In the work of [9] a prototype is implemented introducing an interaction methodology of MR immersive visualization for better decision making in maritime environments. Actually, in such environments large amounts of data are generated by ship-mounted sensors, radar, sonars and ground stations. This work combined 3D visualization in AR head-mounted displays with 2D visualization in tangible table top. It also permits to share updates with collaborators in their tablets and shared wall display. AR displays allow users to overlay information in the real world. The prototype supports also interaction techniques that allow direct manipulation and selection of data to facilitate collaboration. Also, in the work [19], an IA tool for exploring the output of a Dynamic Integrated Climate-Economy (DICE) model is introduced, since it is difficult to visualize such model with complicated data with complex relationships between variables in 2D.

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6 Immersive Analytics for our floods management STrDWO

Our subject of study is characterized by massive data sets as well as uncertain data in time and space which makes our problem rather complex. The generated STrDWO for floods management provides tools to store this big data sets and to analyze them. However such tools are dedicated to computer science experts. In fact, domain expertise have to be integrated to analyze floods data and overcome related problems that arise. Although, domain experts do not know how to manage such tools. Therefore, adapted visualization tools might be developed to not only permit domain expert to visualize data but also immerse in it using advanced immersive analytics technologies. In this paper, we propose a solution in order to know how to properly manage floods data, once a geographical area has been affected by a natural disaster. For this fact, we intend to implement an AR tool to support an interactive visual analytics through a 3D visualization to ensure a better decision-making in this field. This makes it possible to visualize the data and meta-data within the proposed STrDWO. In addition, it also supports visual semantic analysis. This analysis provides the analyst with the advantage to investigate and treat in an interactive way the various complex relationships between different heterogeneous information that exist within our model. Indeed, the reasons behind the use of AR technology is its potential to superimpose real-time live or indirect real-time environments to computer generated virtual imaging information. AR is defined as a technology that allows computer-generated virtual imagery information to be overlaid onto alive direct or indirect real-world environment in real time. Differently from VR, that permits to people to visualize data in computer generated virtual environment, AR bridges that gap between real and virtual worlds in a seamless way. That's why AR will impact potentially the future of many application domains including our case of study. Accordingly, our proposed approach is detailed as follows :

- Various GPS sensors, as well as tracking cameras are located in a real-world environment, at different POIs in order to group the images at every moment, also to track any developments that may alter the steady state for each type of flood waves.
- These real images are transformed into virtual images, once they will be recorded and seen on our system. Indeed, they will be visualized in 3D and in real time on our interactive screens. In addition, these computers have an AR system.
- Once, we detect a change in the visualized image presenting the captured object as a quadruplet (x, y, z, t): where x, y, z are the geographic dimensions at time t of each type of flood waves put under control. It is necessary to initiate interactions with the data stored on the computer that are described according to the model STrWDO to carry out the necessary reasoning about the situation.
- Analysts have the possibility to act collaboratively with the system during the disaster event to launch an alert that calls to the entire environment that

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may be affected by the disaster in order to ensure that the rescue process is in a timely manner. Hence these new visualizations can contribute to solving such issues thanks to augmented real objects.

Our current work represents first steps towards an IA tool for floods management. Understanding floods multidimensional data is of paramount importance and can give insight on future floods management scenarios. IA promise to be more effective than traditional techniques of visualization. We opted for IA also since immersive environments has been successfully used especially for understanding spatial data, letting users visualize large sets of information at once. This was also facilitated with the revolution in low cost immersive AR. We present inhere early work on the visualization system. Our approach is introduced in the figure 5.

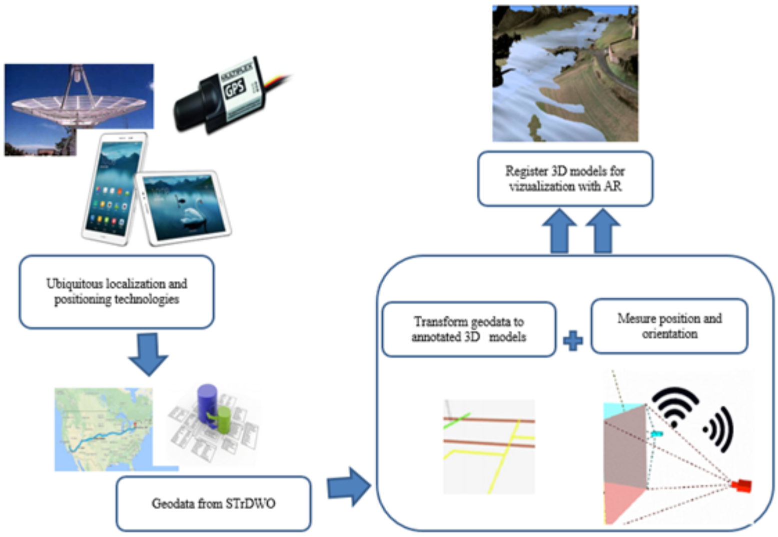

Fig. 5. The approach of visualization of flood trajectory data via AR

From another side, such system is even more informative for environmental decision making and policy analysis. This is because our IA tool supports visual semantic analytics by presenting a new visualization technique making the semantics of this data comprehensible by experts and different stakeholders and more readily communicable to them and facilitating then understanding and engagement of novice users. In fact, the set of data produced in this context is considered as complex and multi-layered. And our tool leaps ahead of this complexity in two phases. Firstly, the back-end of our system, consisting in the proposed STrDWO model, presented data in a semantic way that permit the visualization of additional information including meta-data and aggregated

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summaries of floods data added to relationships between them. Then the AR visualization tool gathers data and different related information in a one encompassing view. And as the AR is a highly interactive technology it permits the investigation of heterogeneous information about floods data and discovery of association between them. The system can display trajectories of the floods among places and on real time and users can interact with it by pointing out locations or points of interest to zoom in and out and then have a view on more or less aggregated data. Users can also launch an alert messages to local competent authorities to take the necessary measures. Also users can execute queries based on the semantic information related to location (streets, cities, etc), time, depth and speed of the flood waves and other parameters. A ranking of the results is also possible. This actually facilitates the search, analysis and comprehension of the presented information and gain in time and accuracy.

7 Conclusion

In this article, we presented a model based on the concepts and the semantic relationships between these concepts, in a subject that takes into account one of the most horrific natural disasters, which is in particular floods. Large amounts of data are generated in this context. Indeed, to obtain the most relevant data related to this domain, we proposed to STrDWO for floods management. Therefore, this problem needs to be solved in real time in order to save as much as possible because time presents here a critical factor. Inspired by recent work in IA, we'll also opt to explore the possibilities offered by new immersive display and interaction technologies. We discussed the possibility of developing a tool based on AR to address this topic by reinforcing the information captured on the affected areas. Implementing this technology would require additional time and is an important aspect of future work for this application. This would allow disaster management professionals to maintain a global and localized view at the same time when viewing the data and making decisions. In addressing many of the challenges, we believe this work provides some important insights into working with big data in AR environments.

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