

Personalized Path Planning Estimation of Georeferenced Urban Scene Considering Criminality Map: the case of Attica

Christos Yiakoumettis ^[0009-0007-4582-5902] and Nikitas Karanikolas ^[0000-0003-1777-892X]

University of West Attica
Department of Informatics and Computer Engineering
{chgiak@uniwa.gr, nnk@uniwa.gr }

Abstract. This paper introduces an advanced georeferenced path planning methodology that enhances urban navigation by incorporating crime statistics to ensure safety and adherence to user preferences. Leveraging a combination of Geographic Information Systems (GIS) and 3D urban modeling, our approach proposes a unique platform that personalizes route planning within the urban landscape of Attica, Greece. Our approach is taking into consideration user's preferences considering qualitative and quantitative features and a Criminality Map. Initially the user profile is estimated based on a pairwise comparison approach of inductive-based learning methodology using Analytical Hierarchy Process (AHP). The proposed platform provides a personalized path planning estimation for urban areas by aligning geographic data with both user-specific preferences and safety considerations. The efficacy of our approach is demonstrated through a detailed case study of Attica (Greece), where over 700 georeferenced models are analyzed for path planning alongside with criminal reports of Police for the year 2022. This research highlights the potential of combining safety metrics with personalization in path planning, offering significant implications for the development of smart navigation systems in urban environments.

Keywords: personalized path planning, urban navigation, virtual tour, GIS systems, criminality map.

1 Introduction

Recent advances in information technology and increased computational power have significantly enhanced the creation of photorealistic 3D models and large-scale scenes, such as those modeling entire urban areas. Concurrently, Geographic Information Systems (GIS) have been popular and familiar for over two decades [30]. Numerous georeferenced 3D models of urban areas have been introduced [30], [32], including some Public Participation GIS (PPGIS) platforms that encourage public engagement [30]. Moreover, personalized virtual tours on GIS platforms (p-GIS), which respect the user's preferences, have been developed [9], [15], [19], [22], [26], [32]. However, one of the primary challenges in viewing large-scale scenes is the

retrieval of information or the estimation of path planning on a 3D georeferenced scene. Additionally, user preferences can be considered through a decision support system to estimate a fully personalized virtual trip in a large-scale georeferenced 3D model [13], [30], [32].

Nonetheless, completing a virtual tour without considering the hard or soft constraints or features of the actual physical scene is much simpler than planning a path for a real-life trip in an urban area. To effectively plan real-life trips in urban environments or modeled georeferenced areas, additional factors must be considered to ensure the trip is both enjoyable and safe. To address this challenge, we propose a path planning estimation for georeferenced urban areas, considering user preferences aligned with qualitative and quantitative features, and the criminality factor of each specific area within the entire urban modeled scene.

Consequently, this paper presents a method of path planning on georeferenced scenes aimed at simulating a realistic and feasible trip in a modeled georeferenced urban scene. This method respects the user's preferences and the georeferenced features of the area, enhancing the enjoyment and safety of the trip. The user's profile is estimated and represented with a set of qualitative and quantitative features that either match or mismatch the features of the buildings (Points of Interest - PoI) as shown in [32] allowing for the estimation of a personalized virtual tour in a georeferenced space. Additionally, a criminality map has been incorporated, applying extra features to buildings or on paths between visiting points. This criminality map assigns a score that reflects the level of criminality of any included model (building, sightseeing, and others) in the specific subarea of the urban modelled scene.

1.1 Case Study of Attica

For our simulation purposes and to demonstrate our work we utilized the extensive region of Attica. Although our approach is location agnostic, Attica region of Greece was selected for demonstration purposes, due to ease access to open data sets. Our approach can be applied to any georeferenced urban area with the proper data sets. We reconstructed over 700 models across this broad area, incorporating features. We collected official crime data for the year 2022 from the police, which was summarized based on police stations per region. Additionally, we gathered official data on the population numbers per municipality from the national population count of 2021. The entire region of Attica was divided into seven regions, as depicted in Fig. 6.

2 Related Work

This paper introduces an innovative platform for path planning within an urban area, considering both criminality and user preferences. This work builds upon the authors' previous work and extends 3D navigation capabilities for georeferenced urban scenes. The algorithm presented is referred to as 'macro-path'. This approach goes beyond merely considering conventional visiting points, such as buildings and sightseeing locations, it integrates user profiles with crime statistics to estimate a safety-oriented

tour path. Despite numerous studies on path planning in urban spaces, none, to our best knowledge, have integrated both personal and safety metrics to customize navigation in georeferenced, modeled urban environments.

2.1 Basic Path Planning Algorithms

The foundation of path planning methodology is built upon classical algorithms such as Dijkstra's [12] and the A* algorithm [14]. While these are pivotal in route planning, their efficiency diminishes with expanding search areas [5]. Innovations have led to more sophisticated approaches like Triangulation A* (TA*) and Triangulation Reduction A* (TRA*) by [11], which optimize pathfinding through Delaunay triangulation and abstraction into simpler roadmap structures, respectively.

2.2 User profile estimation

In the realm of personalization there are approaches that use geometrical or semantic criteria. The combination of both is limited to the known approaches according to the literature review. A system must be able to capture user's preferences and then to satisfy his needs in a known content [2] and [18]. In this study, an ontology-based framework is presented for modelling geographical, user as well as contextual information. Some recent works use ontological models for personalization [19]. Ontologies have been developed using artificial intelligence to facilitate knowledge sharing and reuse and to establish a domain of spatial information [2] and [21].

An ontology-based system allows experts to cooperate with the system, resulting in a list of criteria related to the goal of the personalized modelling. From the perspective of criteria combination, the Analytical Hierarchical Process (AHP) supports the systematic evaluation of multiple criteria, resulting in a hierarchical structure that can help in dealing with the characteristics of personalized preferences [20] and [21], an approach that has already been successfully applied in a 3D Scene Modelling environment [25]. The AHP that allows a systematic evaluation of multiple criteria, resulting in a hierarchical structure that can help in personalized [28]. These last approaches are based on "Hedge Algorithm" which was presented by Freund and Schapire in 1997 [24]. It is known that the best way to gain information about the user's preferences is simply to ask for them [25].

2.3 Personalization in Path Planning

Moving forward many path planning algorithms and methodologies have been presented. Rogers and Langley implement a personalized driving route recommendation architecture based on the Dijkstra's shortest path algorithm, operating on personalized metadata that are approximated by a weighted sum of factors (such as driving time, length, number of turns, and number of intersections) [27]. In addition, Mekni and Moulin present a multi-agent implementation for path planning able to be solved in real time, even under constraints of limited memory and CPU resources [18]. In [17], the route is planned based on user's defined points of interest, which are manually set,

on 3D virtual workspaces. Then, the route is controlled by a set of parameters and a weight is assigned to each of them to regulate their degree of interest. The parameters are either pre-defined by the system or set by the user [16]. Alternatively, the weight values can be defined by constraint satisfaction techniques [4].

The work of [1] gives emphasis on the algorithms for creating a personalized routing plan based on a set of multi-criteria derived from user preferences and geographical information. The algorithm was an on-line weight allocation algorithm, much like the weighted majority algorithm [22] and [23].

An interesting approach to estimate a path for tourists in an urban area using genetic algorithms was presented in 2021. Tourists' objectives were gathered and then ranked using AHP. A genetic algorithm was used to evaluate possible solutions considering the user objectives [10]. Another approach that uses a modernized A* algorithm alongside with a genetic algorithm to find an optimal the route for tourists [29].

Finally, an approach of combining both semantic and geometrical criteria for path planning on a 3D large-scale georeferenced scene has been presented in 2013 [32]. Each building has attached of a set of qualitative or quantitative features that were evaluated by a multicriteria decision support system using a pairwise comparison method to score possible visting points and to select the best possible or avoid irrelative one and match user's profile.

2.4 Smart Cities and Security

Many approaches have been presented related to the architecture, security, and privacy of forthcoming smart cities. Most are centered on real-time data management and the interconnection among devices. Utilizing real-time and big data technologies is crucial. One method involves using IoT technology to collect emerging real-time data, as described in [3]. Another approach for engaging IoT technology to gather data, related to security and privacy was presented in [6].

Additionally, an innovative approach for crime hotspot detection and prediction was introduced in 2020, where authors attempted to forecast crimes using historical data [8]. Progressing from this, an expanded version of the initial platform, aimed at enhancing citizens' security, was launched in 2021 [7].

2.5 Motivation and Contribution

Path planning in an urban area for tourists or citizens looks like an easy process but it's a multi criteria decision. There are many urban simulations and navigation platforms, however all the approaches are ignoring or underestimating the security of passengers and the criminality of the visting area. To address this issue, we present an approach of a personalized urban path planning platform that considers the criminality of the visiting area, based on historical data.

Compared to current approaches in personalized path route planning, our approach considers both geometrical and semantic features of buildings. Moreover, a criminal map is considered in the selection of Points of Interest (PoI) and in selection of the optimal path between selected and highly scored PoI on the planned route.

3 System Overview and Basic Requirements

3.1 Methodology

The presented work is based on an existing path planning platform for 3D modelled georeferenced urban areas. An extension of this work that uses a criminality map is presented on this paper. The wide area of Attica was used as a use case scenario. Therefore, real data about crimes numbers for different regions of Attica was gathered alongside data about the population of these regions. The number of crimes were distributed among the areas, based on official police reports. A criminality map was created and the existing ontological model of features of PoI were updated.

Each point of the map and the containing PoI of it was defined by a Criminality Score, based on criminality map. A Genetics algorithm was used to estimate an optimal path. The fitness function was considering the criminality score of the area of the path alongside geometrical and high-level features of the PoI.

3.2 System Overview

Fig. 1 presents an overview of the proposed personalized route planning decision support system. There are five main components. Our platform is based on google earth GIS platform.

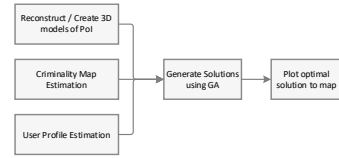


Fig. 1. An overview of the proposed personalized route planning architecture.

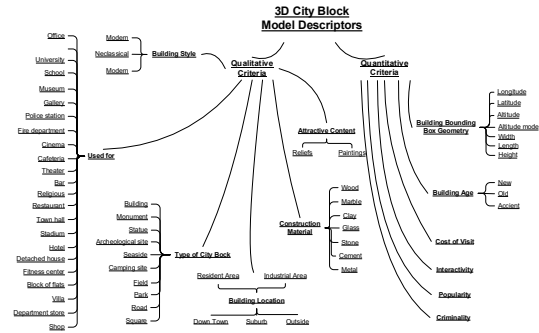


Fig. 2. The set of the metadata is used to describe the geo-referred 3D content.

3D Models of PoI Reconstruction. We developed a customized GIS platform using google API for Google maps and Google Earth. The 3D models of sightseeing were designed using third party applications such as Sketchup. Each 3D model was enriched and with features and added to our platform database.

Criminality Map. To create the criminality maps for the expansive area of Attica, we collected official data on various types of crimes official data on the population of each municipality from the most recent national population count conducted in

2021. We assumed that the population is evenly distributed among the municipalities within each region of Attica. Subsequently, we allocated the annual crime data to each municipality based on its population. The value calculated for each region represents the crime rate and is referred to as the "Criminality Score" in this paper. The Criminality Score for each municipality was determined by dividing the total number of crimes by its population. A higher Criminality Score indicates a higher incidence of crime in that specific region. The final score was normalized across all regions to ensure that the Criminality Scores ranged from 0 to 1 for each region.

The resultant Criminality Map was created and incorporated into the proposed platform as a set of georeferenced polygons. Each polygon covered an entire region and was assigned a specific Criminality Score. Moreover, all models within a region inherited the same Criminality Score as a quantitative attribute. An overview of the Criminality Map generation process is depicted in Fig. 3.

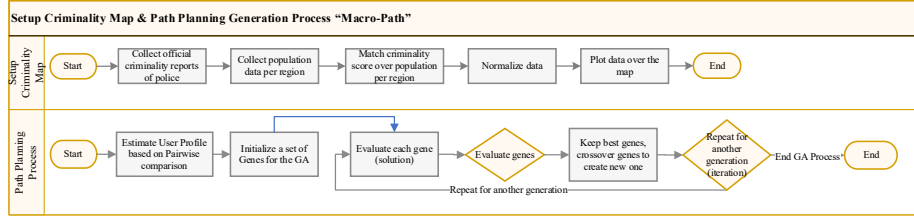


Fig. 3. An overview of the criminality map and “Macro path” generation process

User Profile Estimation. For the user profile estimation, a set of qualitative and quantitative features was used. Among them, there was a feature that represented the Crime Score of the area in which the building is located.

Each reconstructed 3D model has all these features (see Fig. 2). A pair wise comparison method was used to rank features for each user [30]. Afterwards, Analytical Hierarchy Process (AHP) took place to score each model. For model S and for the user u the score is calculated by the equation (1).

$$S(u) = \sum w_u^j f_u^j \quad (1)$$

The top-ranking models were selected for the optimal personalized trip.

Generate Solution – Path Planning Process “Macro-Path”. The last component of our platform is responsible for planning the trip among the selected high-scored PoIs from previous process. For this purpose, a genetic algorithm was used (see Fig. 3). Each genotype contained all the visiting points in the right sequence.

Fitness Function. The fitness function is considering the score of each individual selected visiting point, the emotional and the criminality map of the path throughout the selected points. In addition, the overall distance of the path is considered. The lower the overall distance is, the higher the score of the fitness function is. The emo-

tional criteria of the path are expressed as $E_{n-1,n}$, indicating the score of the nearby buildings of the path between the visiting point N-1 and N. The Criminality Score of the path $C_{n-1,n}$ expresses the score of nearby areas that the selected path between N-1 and N node is taking place. The fitness function is given by the equation (2).

$$Fitness = \left(\frac{E_{0,1} \cdot S_1}{c_{0,1}} + \frac{E_{1,2} \cdot S_2}{c_{1,2}} + \frac{E_{n-1,n} \cdot S_n}{c_{n-1,n}} \right) \cdot DFactor_{path}(d_{overall}) \quad (2)$$

$$DFactor_{path}(d_{overall}) = \begin{cases} 0 & d > OverallMaxDistance \\ OverallMaxDistance - d & d < OverallMaxDistance \end{cases} \quad (3)$$

where $d_{overall}$ is overall distance of the path, $DFactor_{path}$ is a factor that expresses the score of the path based on the distance of it. The $OverallMaxDistance$ is a predefined variable that indicates the maximum possible distance of the path. In case that the distance of the estimated path is more than the $OverMaxDistnce$ threshold, the return score is zero, the chromosome is characterized as invalid, and it is replaced by a valid one.

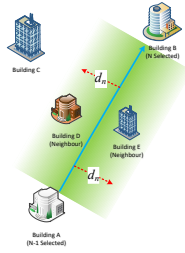


Fig. 4. Distance of a neighbour building between two building.

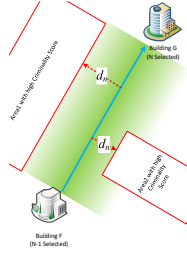


Fig. 5. Distance of a neighbor areas with high criminality score between two buildings.



Fig. 6. Graphical representation of regions of Attica.

A numerical threshold d_n is the perpendicular distance of a neighbor objects to the partial path between the objects n-1 and n. In this context, all objects within the urban scene that are not included in the estimated path are considered as neighboring objects. Additionally, a 3D model qualifies as a 'Neighbor 3D model' only if its specifications align with the user's preferences. In Fig. 4 is shown how the emotional factor $E_{n-1,n}$ is estimated between the Building A and Building B. The distance of Building D is less than the threshold of d_n and the Building D is considered in the cost function as one object of equation (4). On the other hand, Building C is far away from the estimated path. Moving forward, in Fig. 5 is shown how the estimation of factor $C_{n-1,n}$ is calculated and effects overall fitness function in equation (5). The d_n of each Area defined by a criminal score is estimated by the minimum distance between the estimated path and the edge of the specific area.

$$E_{n-1,n} = \sum_{obj} \frac{\sum_i w(i,obj) \cdot f(i,obj)}{NeighbourDistance(obj,r_p)} \cdot DFactor_{partial}(dp_{n-1,n}) \quad (4)$$

$$C_{n-1,n} = \sum_{obj} \frac{\sum_i CriminalityScore(i,area)}{AreaDistance(i,area)} \quad (5)$$

where $obj \in R(r_p)$ and r_p is current point of the path.

$$DFactor_{partial}(dp_{n-1,n}) = \begin{cases} 0 & dp_{n-1,n} > MaxPartialDistance \\ MaxPartialDistance - dp_{n-1,n} & dp_{n-1,n} < MaxPartialDistance \end{cases} \quad (6)$$

where $dp_{n-1,n}$ is the distance between the object N-1 and N. The $DFactor_{partial}$ is a factor that expresses the score of the distance between the buildings. The $MaxPartialDistance$ is a predefined variable that indicates the maximum possible distance between two selected visiting points.

In case that the distance is more than the $MaxPartialDistance$ threshold, the return score of equations (4), (6) is zero and the visiting point S_n is ignored.

4 Platform Implementation

4.1 Implementation Details

Each building model (Point of Interest - PoI) is described using a set of metadata. We represent all 3D objects as a “bounding box” of five faces around the object, excluding the face that points to the ground, regardless of their 3D complexity.

A front-end interface was developed to handle user’s interactions and a back-end module, called GIS Scene Explorer (GIS-SE), based in work of [31], which contains the user’s profile estimation component and the Macro-path estimation process.

4.2 Assumptions

For simplicity and research purposes, we made several assumptions to focus exclusively on the problems addressed in this paper:

- Each 3D model is represented as a simple bounding box with five faces, regardless of its geometrical complexity. Features specific to each building have been attached to each individual face of the model.
- We assume that the distance between two visiting points is a straight line, and that the physical path does not differ in distance from this virtual straight line.

4.3 Implementing Case Study of Attica

We collected official data on crime numbers for the year 2022 from the Police alongside data related to the population of region of Attica clustered per regions. However, the Police’s regions were different than the geographical regions. There was the North-East and the South-East Police regions that overlapped the East geographical region of Attica. Therefore, after normalizing the Criminality Scores for the South and North regions, we distributed the crime numbers to the South-East and North-East regions based on their populations to encompass the entire area of Attica. Furthermore, crime statistics were available for police stations that serve the entire region of Attica; hence, we allocated these crime statistics across the expansive area of Attica,

applying them to all regions based on population density. The total Criminality Score per region is displayed in Fig. 6 and Table 1.

Based on the Table 1 values, a criminality map was created and was considered on the path planning estimation process. This involved initially evaluating each visiting point and subsequently considering the selection of paths among the high-scored visiting points.

5 Discussion and Conclusions

In this paper, we applied a criminality map to a personalized path planning approach for a 3D modeled georeferenced scene of an urban area. The evaluation of the personalized path planning approach itself is not the focus of this paper. The results of our approach will be analyzed under different scenarios: (a) estimating paths without considering criminality maps, and (b) estimating paths that do take criminality maps into account.

Table 1. Criminality Score per Region.

Color	Regions	Num of Crimes	Population	Criminality Score
Orange	North Region of Attica	3.889	526.996	0.026
Yellow	West Region of Attica	6.243	26.759	0.811
Green	Central Region of Attica	10.496	996.283	0.037
Pink	South Region of Attica	4.127	598.847	0.024
Blue	Piraeus Region of Attica	4.442	443.196	0.035
Red	North-East Region of Attica	2687	215.303	0.043
Purple	South-East region of Attica	2.076	301.246	0.024
	Other crimes in Attica	83.556	3.108.630	

5.1 Path Planning Without Criminality Map Case Study

Since many of the sightseeing attractions in Attica are in the city center, we set the Starting Point (SP) to another region with a similar Criminality Score, to compel our approach to choosing more distant visiting points. The Finishing Point (FP) will be the last point of our tour. For demonstration purposes, we assume that users want to explore sites related to Greek history and culture. The algorithm evaluates all the buildings in the area that match the user's profile and calculates the optimal path, considering the distances between selected visiting points. In this scenario, the algorithm first selects the closest building in the Piraeus region that aligns with the user's preferences, then moves on to the nearest site in the Region of West Attica. Afterwards, three more PoI from the Central Region of Attica are selected, with the tour terminating at the Greek Parliament. This process considers only the distance and features of each building, disregarding the Criminality Score and other data from the criminality map. The planned path is illustrated in Fig. 7.

5.2 Path Planning Enhanced with Criminality Map Case Study

In this case scenario, the same SP and user's profile are used. The algorithm assesses all buildings in the area that match the user's profile and considers the Criminality Score. The first visiting point will be the closest building either within the same region or in a region with a similar or lower Criminality Score. The same building was selected as the first visiting point for this case scenario too. As depicted Fig. 8, no building from the West Region of Attica was chosen because the high Criminality Score adversely affected their overall attractiveness scores. Following the initial visiting point, the algorithm selected the nearest building that aligns with the user's preferences from another region with a similar Criminality Score.



Fig. 7. Path without criminality map



Fig. 8. Path with criminality map

5.3 Conclusions

Achievements. The proposed architecture successfully estimates paths for real-world trips that respect user preferences and ensure safety achieving the following.

- estimating criminality maps of an urban area based on real crime data.
- integrating criminality map data into the selection process of visiting points for a personalized path estimation in a large-scale urban scene.
- evaluating path among visiting points to select the safest options for the user.

Limitations. Our architecture operates more efficiently as the criminality map divides the area into smaller segments. The smaller these criminal segments are, the more accurate the results from the path planning process that incorporates criminality map data. In scenarios where numerous models are distributed among regions with varying criminality scores, this architecture proves highly effective.

Future Work. It is important to note that there are additional features that could enhance the path planning process, such as integrating the physical street network. Moving forward, real time crime data reports among regions alongside physical street network could improve architecture efficiency by selecting the safest and most distant from crime scenes physical path within the same region.

Acknowledgements

The publication of the article was fully funded by the University of West Attica (UniWA).

References

1. Allaire, F., Tabouchi, M., Labonte G., Fusina, G.: FPGA Implementation of Genetic Algorithm for UAV Real-Time Path Planning. *Journal of Intelligent & Robotic Systems* Vol. 54, Numbers 1-3, 495-510, DOI: 10.1007/s10846-008-9276-8 (2008).
2. Bell, M., Chalmers, M., Barkhuus, L., Hall, M., Sherwood, S., Tennent, P., Brown, B., Rowland, D., Benford, S., Capra, M., Hampshire A.: Interweaving Mobile Games with Everyday Life. In *Conference on Human Factors in Computing Systems*, pp. 417-426 (2006).
3. Bibri, S., E., Krogstie, J.: The emerging data-driven Smart City and its innovative applied solutions for sustainability: the cases of London and Barcelona. *Energy Inform* 3, 5, <https://doi.org/10.1186/s42162-020-00108-6> (2020)
4. Bonnefoi, P., F., Plemenos D.: Constraint satisfaction techniques for declarative scene modeling by hierarchical decomposition. In: *31A'2000 International Conference* (2002).
5. Botea A., Müller M., Schaeffer, J.: Near optimal hierarchical path-finding. *Journal of Game Development*, Vol. 1, pp. 7-28 (2004).
6. Braun, T., Fung, B., C., Iqbal, F., Shah, B.: Security and privacy challenges in smart cities. *Sustainable cities and society*, 39, 499-507 (2018).
7. Butt, U., M., Letchmunan, S., Hassan, F., H., Ali, M., Baqir, A., Koh, T., W., Sherazi, H., H., R.: Spatio-temporal crime predictions by leveraging artificial intelligence for citizens security in smart cities. *IEEE Access*, 9, 47516-47529 (2021).
8. Butt, U., M., Letchmunan, S., Hassan, F., H., Ali, M., Baqir, A., Sherazi, H., H., R.: Spatio-temporal crime hotspot detection and prediction: a systematic literature review. *IEEE access*, 8, 166553-166574 (2020).
9. Chalvatzis, C., Virvou, M.: Fuzzy logic decisions and web services for a personalized geographical information system. *Studies in Computational Intelligence* 142, pp. 439-450 (2008).
10. Damos, M., A., Zhu, J., Li, W., Hassan, A., Khalifa, E.: A Novel Urban Tourism Path Planning Approach Based on a Multiobjective Genetic Algorithm. *ISPRS International Journal of Geo-Information*. 10(8):530. <https://doi.org/10.3390/ijgi10080530> (2021).
11. Demyen D., Buro, M.: Efficient triangulation-based pathfinding. In: *18th International Conference on Innovative Applications of Artificial Intelligence Conference (AAAI'06)*, pp. 942-947, ISBN 978-1-57735-281-5 (2006).
12. Dijkstra, E.W. :A note on two problems in connexion with graph. *Numer. Math.* 1 Vol. 1, pp. 269–271, (1959).
13. Doulamis, N., Yiakoumettis, C., Miaoulis, G.: Personalised 3D navigation and understanding of Geo-referenced Scenes. In: *IEEE 14th International Symposium on "A World of Wireless, Mobile and Multimedia Networks" (WoWMoM)*, Madrid, Spain, 2013, pp. 1-6, doi: 10.1109/WoWMoM.2013.6583497 (2013).
14. Hart, P., E., Nilsson, N., J., Raphael B.: A formal basis for the heuristic determination of minimum cost paths. *IEEE T. Syst. Man Cyb.* Vol. 4, pp. 100–107 (1968).
15. Kiili K.: Foundation for problem-based gaming. *British Journal of Educational Technology*, Vol. 38, Number 3, pp. 394–404 (2007).

16. Lucas M., Desmontils E.: Declarative modelers. *Revue Intern. de CGAo et d' Infogr.*, pp. 559-585 (2007).
17. Mackinlay, J., Card, S., Robertson, G.: Rapid Controlled Movement through a Virtual 3D Workspace. *Computer Graphics*, Vol. 24, Number 4, pp. 171-176 (1990).
18. Mekni, M., Moulin, B.: Hierarchical Path Planning for Multi-agent Systems Situated in Informed Virtual Geographic Environments. *Second International Conference on Information, Process, and Knowledge Management*, Saint Maarten, pp. 48-55, ISBN 978-1-4244-5688-8 (2010).
19. Nadi, S., Delavar, M.R.: Multi-criteria, personalized route planning using quantifier-guided ordered weighted averaging operators. *International journal of Applied Earth Observation and Geoinformation*, pp.322-3358 (2011).
20. Neustaedter, C., Judge, T., K.: Searching and Content Creation in a Location-Based Treasure Hunt Game. *Technical Report 2011-1116-02* (2011).
21. Neustaedter, C., Tang, A., Judge, T.: The Role of Community and Groupware in Geocache Creation and Maintenance. *CHI '10*, pp. 1757-1766, ISBN 978-1-60558-929-9 (2010).
22. Niaraki, S., A., Kim K.: Ontology based personalized route planning system using a multi-criteria decision making approach. *Expert Systems with Applications*, Science Direct, Vol 36(2), pp. 2250-2259 (2009).
23. Paolis, L., D., Celentano, M., Oliva, L., Vecchio, P., Aloisio, G.: MediaEvo Project: The Life in a Medieval Town, *ACELAE '11*, pp. 22-27, ISBN 978-960-474-286-8 (2011)
24. Papastergiou, M.: Digital game-based learning in high school computer science education: impact on educational effectiveness and student motivation. *Computers & Education*, Vol. 52, Number 1, pp. 1–12 (2009).
25. Rankin J., B., Sandra, S.: A Review of Serious Games and other Game Categories for Education. *SimTecT*, May (2008).
26. Riecken, D.: Personalized views of personalization. *Communications of the ACM*, 43(8), pp. 27-28 (2000).
27. Rogers, S., Langley, P.: Personalized driving route recommendations. In: *Proceedings of the AAAI Workshop on Recommender Systems*, July 26 , Madison, WI, USA, pp. 96–100 (1998).
28. Saaty, T., L.: *Decision Making for Leaders: The Analytic Hierarchy Process for Decisions in a Complex World*. RWS Publications ed. 1990, (ii) (2000).
29. Smirnov, E., Kudinov, S.: Using a Genetic Algorithm for Planning Interesting Tourist Routes in the City on the Basis of Open Street Map Data. *2021 IEEE Congress on Evolutionary Computation (CEC)*, Kraków, Poland, pp. 264-271, doi: 10.1109/CEC45853.2021.9504741 (2021).
30. Yiakoumettis, C., Bardis, G., Miaoulis, G., Plemenos, D., Ghazanfarpour, D.: Collaborative Framework for Virtual Globe Based 3D City Modeling. *Intelligent Computer Graphics 2010*, springer, Vol. 321, pp. 105-122 (2010).
31. Yiakoumettis, C., Bardis, G., Miaoulis, G., Plemenos, D., Ghazanfarpour, D.: GIS Scene Explorer, an Intelligent Navigation Tool for Georeferenced Scenes. *Computer Graphics 2010*, springer, Vol. 321, pp. 165-184 (2010).
32. Yiakoumettis, C., Doulamis, N., Miaoulis, G., Ghazanfarpour, D.: Active Learning of User's Preferences Estimation Towards a Personalized 3D Navigation of Geo-referenced Scenes. *International Journal of Geoinformatica*, Springer, DIO:10.1007/s10707-013-0176-0, pp. 1-36 (2013).