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Human-Aware Planning for Situational Awareness in Indoor Police Interventions

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Abstract. Indoor interventions are among the most dangerous situations police officers have to deal with, mostly due to a lack of situational awareness. This work describes a planner that determines when to provide information, implemented in DLV^K. It is based on the General Tactical Explanation Model, used by Swedish police during tactical interventions. The planner is envisioned to be integrated in an augmented reality tool to enhance officers' situational awareness.

Keywords. situational awareness, human-aware planning, augmented reality

1. Introduction

Police officers deal with many dangerous situations, with indoor emergency interventions being one of the most challenging. Situational Awareness (SA) has been identified as one of the major themes in the existing challenges [1]. SA is about obtaining a thorough understanding of the situation and environment, as well as the projection of future status, and is crucial in decision-making during high-risk situations [2,3].

One way of enhancing officers' level of SA is by providing the proper tools. An automated planner can support officers with deciding where to go and what to do, determining what course of actions would fit the user's goals best. For such an automated planner to be human-aware, it needs to be able to adapt to the goal of the human [4]. This is important in the case of interventions where plans and goals can change constantly.

With this in mind, the research question to be explored is: *How can a human-aware planning system support police officers with interventions for indoor emergencies?*

In this work, we investigate the possibility of planning a path through an indoor emergency. Providing information about the environment can help with increasing officers' SA, assisting them in situations where this is crucial. The planner is envisioned to be integrated in an augmented reality (AR) tool to present the plans and information.

The remainder of this work is structured as follows: The related work and the applied methodology are discussed. The contributions of this work consist of a further problem understanding and a human-aware planner with implementation and evaluation. The discussion and conclusion elaborate on the results and suggest future work.

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2. Related Work

Previous work on logic-based planning often focuses on mobile robots, designing environments for the planner to navigate through [5]. A human-aware planner operates in a space that is populated and affected by human actors [6]. Logic-based planning with a focus on the human-aware aspect includes work on planning towards the promotion of behaviour-change, where a planner is incorporated in an AR environment [7]. Moreover, in the area of plan and goal recognition there is a body of research related to the current work [8,9,10,11,12,13]. Plan recognition as planning, originally introduced by Ramirez and Geffner [8], use planning algorithms to enable an agent to recognise the goals and plans of other agents. Empathetic Planning [9] computes solutions by considering other agents' preferences. In Emotion-aware planning [11], trajectories are generated to transition between mental states, which can be related to the concept of planning for SA. In Active Goal Recognition [10], an agent senses and acts as part of the goal recognition process. While advancing towards its goal, the agent executes sensing and world-altering actions. This relates to the method of supporting SA in the current work. In contrast to previous works, the current work incorporates actions for information retrieval, particularly considering the tactical model, in response to deficient safety conditions.

Earlier work points out difficulties in applying new technologies in the public domain with regard to trustworthiness of both the technology towards the police and of the police towards the public [14,15]. Furthermore, Sanz-Urquijo et. al point out that deployment of AI technologies for law enforcement can come with drawbacks towards the public regarding, among others, discrimination and data safety [16].

3. Methodology

Figure 1 shows the applied methodology of an iterative design process. The first step is to gather sufficient domain knowledge on the problem through a knowledge elicitation process and a literature review. Out of the literature, we selected a model upon which to expand: the General Tactical Explanation Model (GTEM) [3]. These findings are aggregated in the knowledge engineering process. The planner is realised through a logic programming approach. The plans produced by the automated planner inform us on how to deal with the problem or indicate any gaps in knowledge requiring further research.

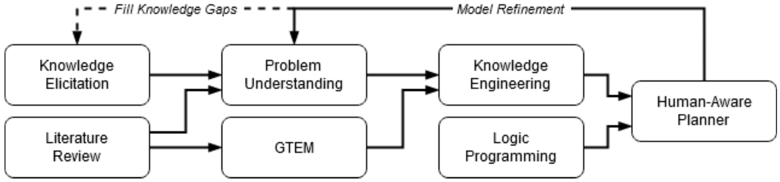


Figure 1. A visualisation of the methodology of the iterative design process

To better understand the problem setting, we elicited meetings with a domain expert on indoor interventions from the police education unit at Umeå University. The goal of these meetings was to develop a shared understanding of the situation and its challenges. Discussed topics include standard protocols, the main goals, and the people involved.

These meeting provided two major themes of difficulty:

- *Information transfer*: providing the available information to everyone is a challenge. Information such as which rooms have been searched can be difficult to convey within appropriate time, but is essential for understanding the situation.
- *Navigation*: from a single-user perspective, it is hard to navigate an unknown building and to properly perceive the situation and environment.

The automated planner can support here by deciding when to show the available information. This would advance the user's understanding of their environment and the situation, making it safer and easier to navigate.

To determine when to show information, we utilise the GTEM. This model is used by police in Sweden in tactical intervention scenarios [3]. One of the main points of focus is on *human limitations*, divided into three areas:

1. *Perception*: perceive the surroundings and people in it
2. *Definition*: define the situation and see whether an attack is occurring
3. *Reaction*: react and respond to the situation within adequate time

The planner is implemented in the logic-based planning language K, which allows for planning under incomplete knowledge [17]. The DLV^K planning system implements K on top of the disjunctive logic programming system DLV. The system is able to solve problems with incomplete initial states [18]. Several example programs using the DLV^K planner are available online[2], such as the Blocksworld domain.

In the planner, a problem is represented using a *program* which consists of:

- `fluents`: the properties of a state that are relevant to a situation
- `actions`: the actions the planner can execute to change fluents
- `always`: the rules specifying the dynamics of change in the planning domain
- `initially`: the conditions that hold at the start of a situation
- `goal`: a set of values for fluents which must hold true when the planner converges

4. Human-Aware Planner

This section defines the different parts of the planner. The operating space and the states in it need to be defined properly and it needs to be clear how to transition between states and what the properties of a produced plan are.

We first introduce fluents, which are a way to describe the world (i.e. the state space). They convey properties of entities in the world that are deemed relevant to the domain.

Definition 1 *The set of fluents $F = \{f_1, \dots, f_n\}$ consists of all variables in the environment that are relevant to the state space.*

Considering fluents, we define the operating space of the planner. A state in this space is characterised by a combination of the fluents' values. State transitions are realised by taking actions to change or update the fluents.

Definition 2 *A state $s_i = \{f_1 : x_1, \dots, f_n : x_n\}$ is a mapping from fluents to values, where each fluent f_i is mapped to a value x_i. Each state in the state space consist of a unique combination of values for fluents.*

[2]URL: https://www.dbai.tuwien.ac.at/proj/dlv/K/

Definition 3 *Given two states in the state space S: s_i and s_{i+1}, with $s_i \neq s_{i+1}$, an action $a \in A$ causes a transition (s_i, a_i, s_{i+1}), where the current state of the planner changes from s_i to s_{i+1} by executing action a_i.*

The planner then has an initial state and a goal state that are part of the state space, a set of fluents, and a set of actions. It produces a plan to navigate towards the goal state. The execution of a plan results in a trajectory (a path) from an initial state to a goal state.

Definition 4 *A planner Pl is a function $\langle S_I, S_G, F, A\rangle \rightarrow P$ with S_I the initial state, S_G the goal state, F the set of fluents, A the set of available actions, and P a produced plan.*

Definition 5 *A plan P is a sequence of actions $\langle a_1 \ldots a_i\rangle, i \geq 0$ which, if executed in order, provide a trajectory through the state space to reach the goal state S_G.*

5. Implementation

A characterisation of the described system is implemented in the planning language *K*. Figure 2 visualises the use case. It contains a building with several rooms. Room `C1` is the starting position and room `R9` is the goal state. Room `C5` contains a warning, indicating a potential dangerous situation which would require a higher level of SA before entering.

The values in each room are an indication of the obstacles of gaining *perception*, *definition*, and *reaction* insights there, with a higher value indicating a higher difficulty (e.g. room `C5` has higher obstacle values, since there is a potential dangerous situation).

All code and map visualisations are available online[3].

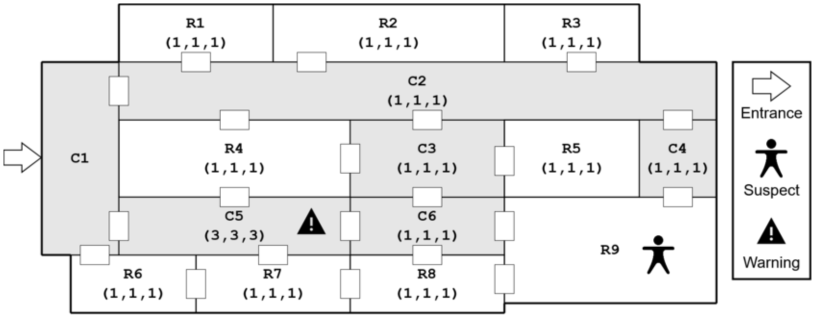


Figure 2. Map of the use case environment

5.1. Background Knowledge

The background knowledge consists of the fixed values. This information is predetermined and depends on the use case. First, it contains the spaces and the accessibility between them. The background on the spaces consists of an id and three integers. These correspond to the three obstacle levels. All rooms have some inherent difficulty in entering, therefore all rooms have basic obstacle levels of 1. To safely enter a room with

[3]URL: https://github.com/joostvossers/HAP-SA

a warning indication, the user will need to overcome more obstacles - they should only enter if their SA of the situation has been appropriately increased. Therefore, the obstacle levels for a room with a warning sign are set to 3. Since rooms `C1` and `R9` are the initial and goal state, they have not been given inherent obstacle values.

5.2. Planner

The implementation of the planner follows the *program* structure, described in Section 3.

The first part of the planner are the fluents. These are the values that can change or be changed throughout the plans. We identify the following fluents:

- The user's current location, as a space in the environment
- The user's indication of SA, divided into *perception*, *definition*, and *reaction*.

```
current_loc(L) requires space(L, _, _, _).
perception_level(P) requires #int(P).
definition_level(D) requires #int(D).
reaction_level(R) requires #int(R).
```

The available actions are divided into two parts. First, we need to be able to move through the environment. The remaining actions consist of actions that are used to increase the *perception*, *definition*, and *reaction* levels. How exactly these levels are increased depends on the specific domain and use case. In this case, the focus is on *when to take which action*, for which the basic 'increase' actions should suffice.

```
move(L) requires space(L, _, _, _).
increase_perception(X) requires #int(X).
increase_definition(X) requires #int(X).
increase_reaction(X) requires #int(X).
```

How the fluents change based on the execution of an action is defined in the `always` section of the implementation. It also specifies rules and constraints for the execution of certain actions. Together, the section consists of three parts:

- tracking the *perception*, *definition*, and *reaction* levels
- moving through the environment
- the inertials: fluents that need to stay consistent after the planner takes an action

The three levels are updated in the same manner. After a move to a new space, they are set to 0 because of the assumption that the user has no prior knowledge on the newly entered room. The levels can be increased one step at a time, with a minimum of 0 and a maximum of 3. As an example, the rules for updating the perception level look like this:

```
caused perception_level(0) after move(L).
caused -perception_level(P) after move(L),
    perception_level(P).

caused perception_level(X) after increase_perception(X).
caused -perception_level(X) after increase_perception(X1),
    perception_level(X), X1=X+1.
executable increase_perception(1) if perception_level(0).
```

```
executable increase_perception(2) if perception_level(1).
executable increase_perception(3) if perception_level(2).
```

For the `move` action to be possible, the new location needs to be accessible from the current location and, most importantly, the *perception*, *definition*, and *reaction* levels of the user need to be high enough to safely enter the next space.

```
executable move(L1) if acc(L1, L2), current_loc(L2),
    space(L1, P, R, D),
    perception_level(P1), P1>=P,
    reaction_level(R1), R1>=R,
    definition_level(D1), D1>=D.
```

The starting state consists of the starting values for the determined fluents. In this case, the user's start position is room `C1` and the *perception*, *definition*, and *reaction* levels are set to 0. The goal state contains the desired values for certain fluents. The final state of a plan should include the values for these fluents for it to be considered successful. In the use case, the user should get to room `R9`, the room with the suspect.

6. Evaluation

To evaluate the planner, we use the environment presented in Figure 2. The planner generates plans of sequential actions through the space. If executed, these result in the goal (i.e. ending in room `R9`) being reached. We identify three of these possible plans and compare them with the straightforward, intuitively fastest way. The plans are:

- *Fast*: `C1` → `C5` → `C6` → `R9` (Figure 3)
- *Plan 1*: `C1` → `C2` → `C4` → `R9` (Figure 4)
- *Plan 2*: `C1` → `C2` → `C3` → `C6` → `R9` (Figure 5)
- *Plan 3*: `C1` → `R6` → `R7` → `R8` → `R9` (Figure 6)

Depending on the specifics of the environment, different paths can be favourable against others. We compare the paths with each other on three different scenarios:

- There is no additional warning in any of the rooms
- There is a warning for potential danger in room `C5`
- There is a warning for potential danger in room `C6`

In case of a warning on the path, the user needs to receive additional information to increase their *perception*, *definition*, and *reaction* levels (i.e. their SA).

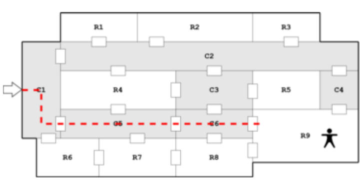


Figure 3. The trajectory of the fast plan

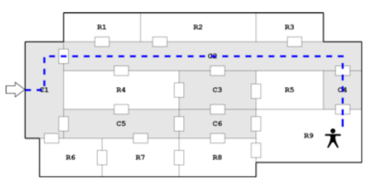


Figure 4. The trajectory of plan 1

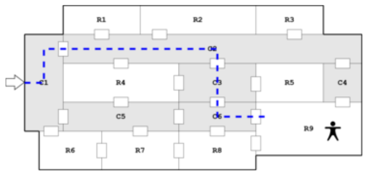


Figure 5. The trajectory of plan 2

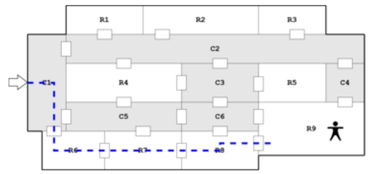
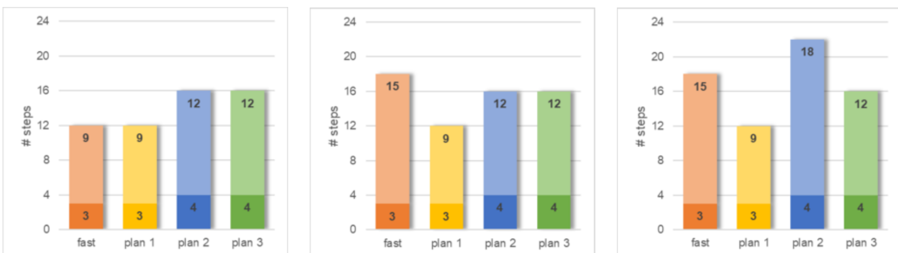


Figure 6. The trajectory of plan 3

The amount of steps for the four paths in the three different scenarios are shown in Figure 7. The bottom part of the bars are the `move` actions and the top part are the `increase` actions. We can see that for the scenario without additional warnings, the fastest path is one of the most optimal, which is in line with expectations. In the other scenarios, there is always a path from the planner that is favourable over the fastest path. In fact, the fastest path is never strictly preferred over all three alternatives.



(a) No warning (b) Warning in `C5` (c) Warning in `C6`

Figure 7. A comparison of the amount of steps necessary to traverse the paths through the different scenarios

7. Discussion

The aim of this work was to construct a planner to support police officers during indoor interventions. The foundation for the planner lies in the GTEM, which models human limitations in *perception*, *definition*, and *reaction*. Based on these levels and a specified environment, the automated planner provides a plan through the intervention including the necessary extra steps to keep an appropriate level of SA. The current implementation is straightforward, but versatile. It is easily adaptable to a new environment and more constraints on the system actions can be added without too much difficulty.

The planner can support police officers by deciding *what* kind of information is necessary at *which time*. The calculated plans are supposed to be part of a bigger system which incorporates them in a virtual environment. In-the-field applications of AR technologies have been suggested [19,20,21,22], as well as its applicability in training [23,24]. Police officers and experts see the possibilities and are willing to test and incorporate these tools in their routines [25,26]. Figure 8 visualises an interpretation of the AR environment on top of the planning system. Some examples of additional information are shown, such as the line on the floor and the warning on the left. This visualisation provides an intuition on the tool. An actual implementation for an AR system should include more extensive research on what information officers want to see.

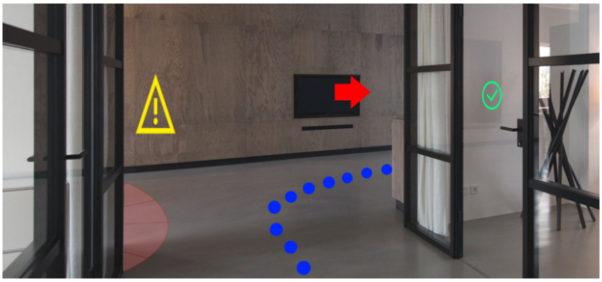


Figure 8. A visualisation of vision through the AR glasses in an office space[4]

With visual tools, it is important to construct ones that are *helpful* rather than *intrusive* and that do not distract from the main task. Special attention should be paid to not overstimulate the user and to keep their workload as low as possible [27].

The extra information that is presented to the user guides them while keeping in mind their SA. The planning system is human-aware in that it is based on the GTEM model, which is about dealing with *human limitations* in situations like this. The planner and the AR environment together can guide the user safely through the intervention.

A limitation in our implementation is in the `increase` actions. It is more intuitive to define real actions that elicit specific information. This would require more research into what officers want in these situations. Our implementation provides a framework for dealing with indoor emergencies and constructs plans on *when* to present information relevant to the scene. *What* information is presented is left to the specific use case.

Lastly, it is important to ensure transparency of the system. It should be clear how the planner comes to a plan and why it decides to prioritise certain actions. More transparency also increases the trust that police officers have in the system. As mentioned before, deploying new technologies in the public domain can result in undesired changes for the public, such as a decrease in privacy and data safety. Therefore, the ways in which the `increase` actions and the rest of the system are realised should be deliberately discussed with domain experts and the people affected in general.

8. Conclusion

This work presents a human-aware planner to support police officers during interventions for indoor emergencies. The planner models the environment and provides a plan for how to move through it. More importantly, it strives to heighten the user's sense of SA by determining at which moment to show extra information about the situation and environment. The planner is intended to be integrated in an AR tool where this extra information is virtually provided to the police officer.

Future work should explore specific types of information to present. This requires a more intensive cooperation with police officers to learn about their needs and preferences for such a tool. The next step to extending this work would be the creation of a 3D environment for the envisioned AR system. This would allow for a more extensive evaluation with police officers to see if the planner meets their requirements.

[4]Original image from Nastuh Abootalebi, Unsplash, URL: https://unsplash.com/@sunday_digital

References

[1] Borglund EA, Hansson J. Active shooter events, a challenge. In: Information Systems for Crisis Response and Management Conference; 2023. .

[2] Endsley MR. Design and evaluation for situation awareness enhancement. In: Proceedings of the Human Factors Society annual meeting. vol. 32. Sage Publications Sage CA: Los Angeles, CA; 1988. p. 97-101.

[3] Borglund EA, Hansson J. Tactical police interventions: design challenges for situational awareness. In: ISCRAM 2022, 19th International Conference on Information Systems for Crisis Response and Management, Tarbes, France, May 22-May 25, 2022; 2022. .

[4] Cirillo M, Karlsson L, Saffiotti A. Human-aware task planning: An application to mobile robots. ACM Transactions on Intelligent Systems and Technology (TIST). 2010;1(2):1-26.

[5] Yang F, Khandelwal P, Leonetti M, Stone PH. Planning in answer set programming while learning action costs for mobile robots. In: 2014 AAAI Spring Symposium Series; 2014. .

[6] Chakraborti T, Sreedharan S, Kambhampati S. Human-aware planning revisited: A tale of three models. In: IJCAI-ECAI XAI/ICAPS XAIP Workshops. vol. 10; 2018. .

[7] Brännström A, Kampik T, Nieves JC. Towards human-aware epistemic planning for promoting behavior-change. In: Workshop on Epistemic Planning (EpiP)@ ICAPS, Online, October 26-30, 2020; 2020. .

[8] Ramırez M, Geffner H. Plan recognition as planning. In: Proceedings of the 21st international joint conference on Artifical intelligence. Morgan Kaufmann Publishers Inc; 2009. p. 1778-83.

[9] Shvo M, McIlraith SA. Towards Empathetic Planning. arXiv preprint arXiv:190606436. 2019.

[10] Shvo M, McIlraith SA. Active Goal Recognition. In: AAAI; 2020. p. 9957-66.

[11] Brännström A, Nieves JC. Emotional Reasoning in an Action Language for Emotion-Aware Planning. In: International Conference on Logic Programming and Nonmonotonic Reasoning. Springer; 2022. p. 103-16.

[12] Rao AS, Georgeff MP, et al. BDI agents: from theory to practice. In: Icmas. vol. 95; 1995. p. 312-9.

[13] Keren S, Gal A, Karpas E. Goal recognition design. In: Twenty-Fourth International Conference on Automated Planning and Scheduling; 2014. .

[14] Paulsen JE. AI, trustworthiness, and the digital Dirty Harry problem. Nordic Journal of Studies in Policing. 2021;8(2):1-19.

[15] Engelbrecht H, Lukosch S. Dangerous or desirable: Utilizing augmented content for field policing. International Journal of Human–Computer Interaction. 2020;36(15):1415-25.

[16] Sanz-Urquijo B, Fosch-Villaronga E, Lopez-Belloso M. The disconnect between the goals of trustworthy AI for law enforcement and the EU research agenda. AI and Ethics. 2023;3(4):1283-94.

[17] Eiter T, Faber W, Leone N, Pfeifer G, Polleres A. Planning under incomplete knowledge. In: International Conference on Computational Logic. Springer; 2000. p. 807-21.

[18] Eiter T, Faber W, Leone N, Pfeifer G, Polleres A. A logic programming approach to knowledge-state planning, II: The DLVK system. Artificial Intelligence. 2003;144(1-2):157-211.

[19] Apostolakis KC, Dimitriou N, Margetis G, Ntoa S, Tzovaras D, Stephanidis C. DARLENE–Improving situational awareness of European law enforcement agents through a combination of augmented reality and artificial intelligence solutions. Open Research Europe. 2021;1.

[20] Bang J, Lee Y, Lee YT, Park W. AR/VR based smart policing for fast response to crimes in safe city. In: 2019 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct). IEEE; 2019. p. 470-5.

[21] Haque SEI, Saleem S. Augmented reality based criminal investigation system (ARCRIME). In: 2020 8th International Symposium on Digital Forensics and Security (ISDFS). IEEE; 2020. p. 1-6.

[22] Ayyanchira A, Mahfoud E, Wang W, Lu A. Toward cross-platform immersive visualization for indoor navigation and collaboration with augmented reality. Journal of Visualization. 2022;25(6):1249-66.

[23] Zechner O, Kleygrewe L, Jaspaert E, Schrom-Feiertag H, Hutter R, Tscheligi M. Enhancing operational police training in high stress situations with virtual reality: experiences, tools and guidelines. Multimodal Technologies and Interaction. 2023;7(2):14.

[24] Amorim JA, Matos C, Cuperschmid AR, Gustavsson PM, Pozzer CT. Augmented reality and mixed reality technologies: Enhancing training and mission preparation with simulations. In: NATO Modelling and Simulation Group (MSG) Annual Conference 2013 (MSG-111), 2013; 2013. .

[25] Engelbrecht H, Lukosch SG. Viability of augmented content for field policing. In: 2018 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct). IEEE; 2018. p. 386-9.

[26] Hoevers M. The potential of augmented reality glasses in the practice of street policing: an experimental study among dutch (mounted) police officers. University of Twente; 2021.

[27] Sanquist T, Brisbois B, Baucum M. Attention and situational awareness in first responder operations. Pacific Northwest National Laboratory, Alexandria, VA. 2016.