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DECISION SUPPORT SYSTEM FOR SEARCH & RESCUE OPERATIONS

Abstract *SAR (Search and Rescue) operation is a complex process, often carried out in the absence of resources and time. Every single minute matters, as it puts the lost person in more danger. Therefore, it is really crucial to plan and coordinate SAR operation effectively. Because the search area is often very extensive, any leads about where to look first are invaluable. This can be achieved by modelling lost person's behaviour based on the data from past operations. Generated results present probabilities of finding a subject in different segments of the search area, which might benefit the planning and the execution phases of the operation. The authors evaluate one of the commonly used modelling methods and propose several ways to improve it, together with some preliminary evaluation results and an already implemented system, which incorporates the described methodology.*

Keywords Decission Support System, SAR, GIS

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1. Introduction

The goal of SAR operations is to locate and provide medical assistance for individuals in distress. A typical operation consists of three stages: gathering information about a missing person (subject), planning the operation and executing the plan in the field. The main problem of SAR rescuers is the lack of current location of the subject and the limited amount of manpower to perform an extensive search.

It is a role of the incident commander to decide how to assign teams to search segments and which areas should be looked in the first place. For many years these activities have been conducted mostly using a paper map, a pen and the experience of the commander alone. However nowadays it is possible to design and implement decision support systems, which can process big amounts of data and look for hidden patterns not visible at the first sight.

Such system has been designed and implemented with the cooperation of the polish mountain rescue service GOPR and has already been incorporated into their daily activities. It uses data from past operations and creates maps with probabilities of finding a subject in the search area. Having such maps combined with the incident commander's knowledge might be really beneficial in order to split the resources in an optimal way.

The aim of this paper is to present the behavioural modelling approaches, especially those suited for modelling a lost person behaviour, together with some preliminary evaluation results of one of the method using local specific data and several concepts, which might increase the effectiveness of the modelling with their own evaluation.

The paper is organized as follows. The first section briefly describes the research behind the lost person behaviour and the motivation of behavioural modelling. It is followed by a brief description of GIS systems and spatial analyses. Next chapter describes the modelling approach, which has been implemented, overviews all currently known models and gives one detailed example of a model calculation routine. Next section overviews the existing system and its implementation aspects. Afterwards, the preliminary results of the modelling evaluation are presented together with several ideas for improving the method and their preliminary evaluation. Subsequently, the implemented system and other existing solutions are described, which is followed by the research direction and conclusions.

2. Lost person behaviour

Planning and executing a SAR operation might be treated as a spatial problem, because many decisions taken by both the subject and rescuers are influenced by the terrain. The subject became lost after making certain spatial decisions, so it might be possible to simulate those using GIS data. Numerous papers like [5, 6, 11] argue that lost people think schematically and after analysing enough data some reoccurring patterns emerge. Studies on lost person behaviour allowed researchers to split individuals that show similar behaviours when they become lost into categories related to their age, fitness and interests, like young child, skier or hiker.

Unfortunately those patterns do not repeat every single time, which means that SAR operations are subject to a high degree of uncertainty. With the time going by the area, which could have been reached by the subject gets bigger, so the uncertainty becomes even higher. That is why acting fast and proper distribution of resources play so crucial role.

Despite of the high level of uncertainty, it is possible to forecast future incidents and areas, which are more susceptible to be treacherous. Such study has been presented in [2] and supported by more than 200 incidents. The authors also claim, that those areas change with weather conditions and seasons, which introduces more parameters for the modelling, so that it becomes more accurate. However in order to proceed with the modelling, which depends on the geographical data, one needs to use a GIS system.

3. GIS

GIS systems have been designed to create, store, analyse and visualise the spatial data. Their key element is the data they are using, which has to be of the highest quality and resolution in order to not misrepresent the objects it features. That is why some authors, like [10], claim that getting and preparing proper data takes up to 80% percent of project's time.

After preparing the data, the next step is to ensure its high availability, which can be achieved by importing it into a spatial databases. Modern databases with their replication mechanisms, concurrent use and backup systems secure the invaluable data and provide quick and easy access to it.

When it comes to analysis, it is usually done in one of two ways. Either a database engine is used to perform geographical transformations using SQL queries or the data is supplied to an application engine, which performs the operations requested in a script. Both solutions have their pros and cons, however the application engine, which is highly optimised just for the purpose of data manipulation, usually performs better.

Using a separate application just for the data manipulation comes with additional benefits of being able to visualise both input and output data and to conduct interactive analyses, which might be stopped at any given moment. It is a useful functionality, especially when processing times span between minutes and hours, so in case of an error, it is beneficial to spot it as soon as possible and fine tune the processing chain before the end of evaluation.

Two most popular and widely used database engines are PostGIS and SpatiaLite. The most commonly used application engines are ArcGIS and QuantumGIS.

4. Behavioural modelling

One of the approaches for modelling lost person behaviour has been described in [7] and is based on the incidents from the International Search and Rescue Incident Database (ISRID). It contains about 50 000 entries, which have been divided into subject categories e.g. hiker, hunter, autistic child, person with dementia. The data consists of summary statistics for each category representing how lost people behaved in unknown terrain, including typical decisions they took like walking direction, whether to stick to the trail or not, or how long one should be mobile. All models, apart from the find location model, have a quartile statistics structure. It means that the search area is divided into four categories representing zones with 25%, 50%, 75% and 95% probability of finding a subject (the 95% probability has been used because some individual extreme cases could have introduced perturbations, so in order to avoid them, they had been excluded). An example extraction from the track offset model data is presented in the Table 1.

Table 1

Extraction from the track offset model data, the values represent distances in meters.

Category	25% Probability	50% Probability	75% Probability	95% Probability
Dementia	4	15	71	307
Hiker	50	100	238	424
Hunter	50	100	200	380
Mental Illness	None	23	None	None

In order to use the statistics to create the probability zones, which could be projected on a map, they had to be implemented as geoprocessing routines, which require a lot of spatial information such as terrain topography, water features, obstacles, roads and trails etc. One example of the discussed models is the track offset model. It requires linear features (LF) such as roads, trails and the area of interest (AOI) and returns a layer with probability density of finding a subject depending on proximity to those features. Its geoprocessing routine is following:

1. `Query the database for distances for the Track Offset model (Table 1)`
2. `Load vector layers with the LF and the AOI`
3. `Extract the AOI from the LF`
4. `Calculate Euclidean distance (EUC) between the linear features (this procedure creates a raster layer with values representing distance in meters between a processed pixel and its closest feature)`
5. `Create a table with distances and their probabilities according to data from Table 1 (e.g. distances between 0-50 m → 25%, 50-100 m → 50%, 100-200 m → 75% and 200-380 m → 95% as for the hunter category)`
6. `Remap values from the EUC raster according to the previously created table (e.g. 17 m → 25%)`
7. `Create a raster layer with probability density, calculated in such way, that pixels in different probability groups get probability density coming`

`from a division of the probability held by the considered group (the 25%, 50%, 75% groups contain 25% probability, the 95% group contains 20% probability) by the total number of pixels in this group.`

After calculating probability zones and dividing them by the area they occupy one gets the probability density of finding a subject in each area. However before the models can be more information is required. It consists of an initial planning point (IPP), which is the point where the subject was last seen or the point of subject's last known location and a rendezvous point (RP), which corresponds to subject's destination or the place he or she was supposed to meet with the group.

The list of models proposed in [7] together with sample visualizations illustrated in Figure 1 (the central point is the IPP and the south-east point is the RP):

- **Horizontal Distance from IPP** – probability of walking a certain straight line distance from IPP.
- **Elevation Distance from IPP** – probability of height change during march.
- **Horizontal Change from IPP** – probability of walking a certain distance, depending on the slope type: uphill, downhill, no slope.
- **Dispersion Angle** – probability of changing a march direction.
- **Track Offset** – probability of staying on or close to a line feature such as road, trail, river, stream, power lines.
- **Mobility** – probability of reaching different zones depending on subject's march speed, accounts for trails and roads, which increase travelling speed and for obstacles like precipice or dense forest, which decrease it.
- **Find location** – probability of finding a lost person in a characteristic place like pond, abandoned house, barn, e.g. autistic children are attracted by light reflections, so they are often found near water features.

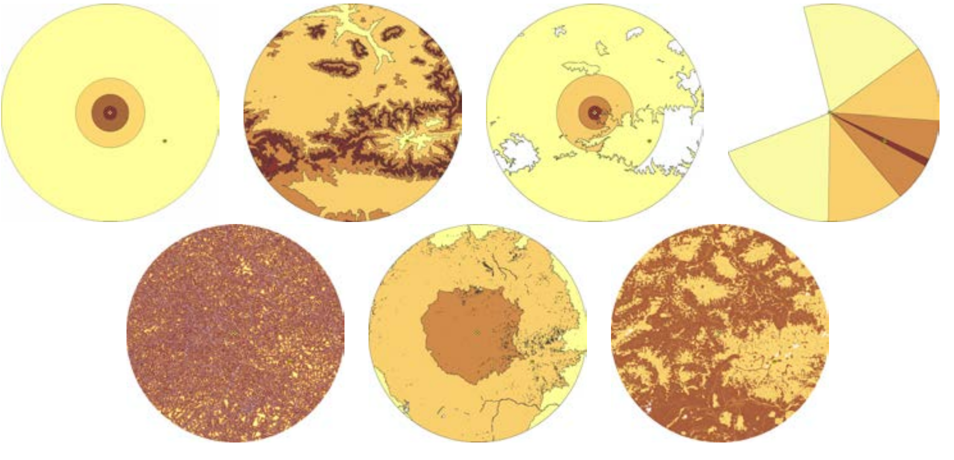

Figure 1. Behavioral model visualisations.

In the visualisation in Figure 1 areas with more intense colour represent low probability areas, but high probability density. Considering the horizontal distance from IPP model, the zone with the most intense brown tint represents a 25% probability zone. However because it covers significantly less area than the other zones, the probability density of finding a subject in that area is higher and therefore it should be searched in the first place. The last presented visualisation depicts the find location model, which represents probability of finding the subject in proximity to different terrain structures like abandoned buildings or roads and areas, such as woods or fields. In that model each structure has its own probability (varying from 1% to 31% depending on the category), so it is the only model, which does not have the quartile statistics structure. The proposed models rely on different terrain features, which are taken into consideration when a lost person makes decisions. In order to create summary statistics probability densities from all the models need to be summed up in a combined probability model. During the summation all models are equally important. The final model can be later mapped into search segments with probabilities calculated separately for each segment. This mechanism is demonstrated in Figure 2.

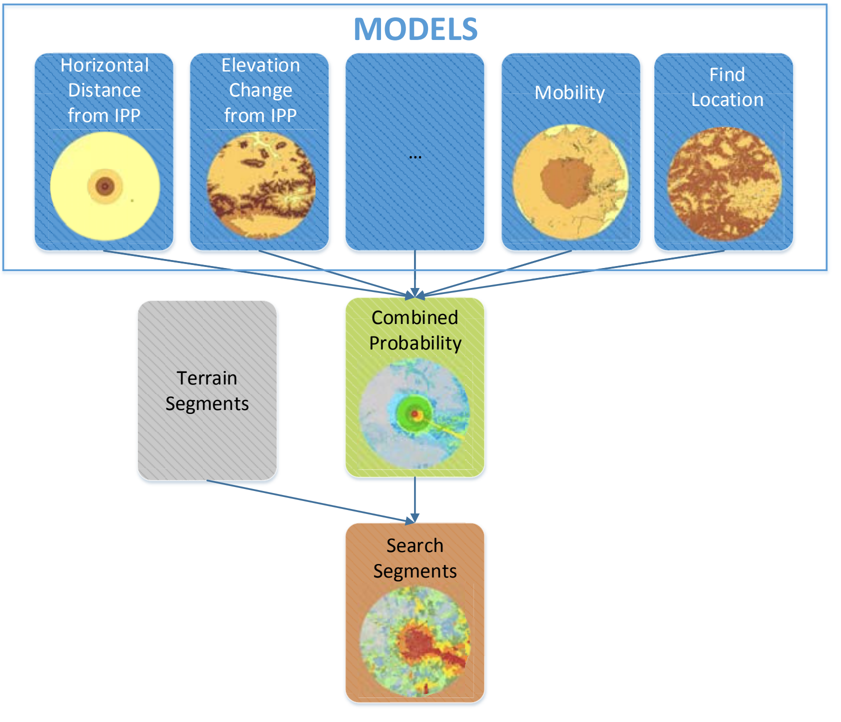

Figure 2. Diagram with models combining mechanism.

5. Method evaluation and possibilities of improving its accuracy

Presented methodology has been preliminarily evaluated using local specific data supplied by the mountain rescue service GOPR from the Podhale area. 10 successfully finished operations have been randomly selected from the set of over 200 SAR operations. The operation had to end with finding a subject in order to compare his or her find location with the probabilities generated by the models. After calculating the probabilities for the search segments given the input data from the archived reports, the segments have been ranked according to their probabilities. The score of the result has been defined as a position of the segment within top x% segments of the rank.

For 7 cases the segment with subject's find location was in the top 30% of all segments, for 2 cases it was in the top 15% and the last one was in the group of top 50%. The results are illustrated in Figure 3. The Y axis should be understood as a position in ranking divided by the total number of segments, so the lower the better. They show that the accuracy of the method in most cases is quite high. The most important feature of the results is that it is not misleading and pointing to wrong areas, because even at the lowest score, only half of the search area would have been needed to search through.

In order to generate those results a standard approach of assigning only one subject category and assuming that all models have equal weights has been taken. However applying a fuzzy logic approach and taking several categories with weights may be closer reality and generate better results. With the new approach it might be possible to create categories such as despondent hiker with dementia or autistic skier. Even though some combinations may not make much sense, there is a possibility that some other ones will correspond to the subject's real profile much closer.

Because the archive data assumed, that only one category can be assigned, it was impossible to directly extract other categories or weights. The additional categories and their weights were selected, so they could match the missing person profile as close as possible. The maximum number of selected categories was chosen arbitrary as 3, but for most cases only 2 categories were used. The weights were also chosen arbitrary as values, which sum up to 100 (e.g. Hiker 70, Autistic 20, and Despondent 10). Adopted model assumed one main category and two additional ones with a smaller influence.

After recalculating all the models the change in the score was not big enough and not consistent to give a conclusive answer whether the method improved the results or not. The main reason was probably weights selection, which was done arbitrary.

The next tested scenario was to assign weights for the models and to use single category selection, as the multiple categories usage has not improved the scores substantially. The range of possible weights was between 1 (default) and 5. In all cases only 3 weights were changed from default values. Those were Horizontal Distance from IPP – 4, Mobility – 3, Track Offset – 2. The results have been more substantial and on average all scores have improved by about 5%.

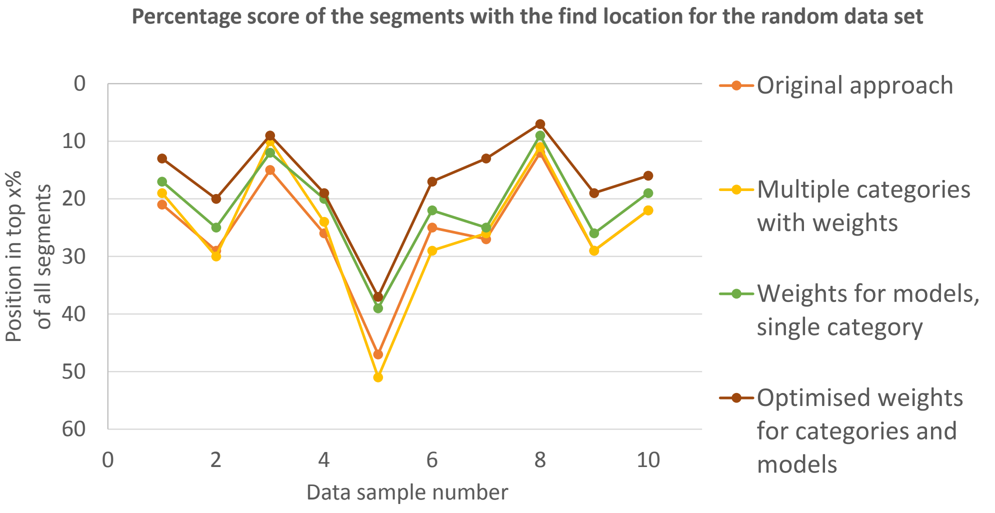

Figure 3. Scores of the data samples.

The final attempt to improve the scores was made using an evolutionary algorithm $(\mu+\lambda)$, which was used in order to find the optimum set of parameters for both categories and models. The problem defined in such way is both linear and not that difficult to solve with a brute force approach, however the calculations take a lot of time, so this approach was supposed to use this time more effectively and reach the optimum solution faster than with the brute force. The quantitative parameters of the simulation were set quite low. The population consisted of 20 individuals and the number of iteration was set to 30.

Even using such low parameters gave a great result. The scores improved on average by about 10%. The reason behind using this method was to see how much further the scores can be improved, without using a blind search and also to see if there are any re-occurring patterns in the parameters values, which might give a hint on how the parameters should be selected for the future work. Unfortunately the data sample was too small to give any definitive answers and this approach will have to be investigated further. The framework used in evolutionary calculations has been described in [4].

The next step will be to apply the presented methodology on the entire data set, so more than 200 cases and to apply other methods to look through the solution space. It would be also very useful to create a map of the solution space for at least one data sample using brute force with strong constraints on the parameter values and see how it changes.

A similar study has been published recently for the Yosemite National Park and can be found in [1]. The approach however is a little bit different. The authors tried to determine whether using statistical values for the models from their own collection might have improved the results for their area. They received some significant results when it comes to improving the accuracy of the Horizontal Distance from IPP and the Mobility models. They encourage to use local specific statistics, however in case of not having any local specific data the authors' advice is to use the data from [7].

6. Prototype system

In order to support the planning stage of SAR operations, a planning m+odule has been designed and implemented [12]. Its core element is a python extension for Esri ArcMap (which is a part of the ArcGIS platform). It invokes python scripts containing geoprocessing chains for the models. The geoprocessing is implemented using the python module Arcpy provided by Esri. In order to compute a model the scripts need to be supplied with the statistical data from project's database. Results from the computation may later be saved as output layers to a storage. When the layers are computed and saved, they can be displayed in ArcMap and help SAR experts plan the operation and support field decisions. The data coming from the database contains the summary from previous SAR operations. The architecture of the solution is illustrated in Figure 4.

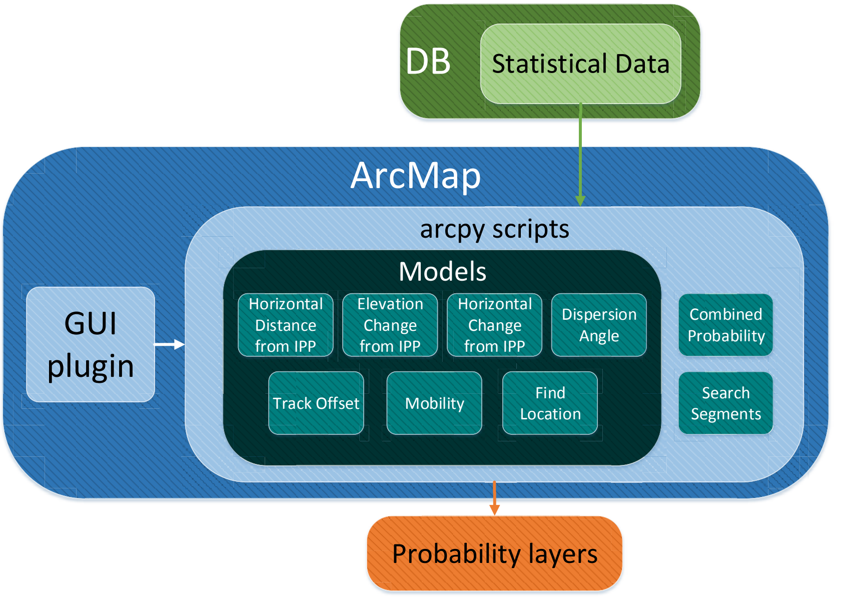

Figure 4. Diagram with the prototype system architecture.

This architecture has already been tested and is being used by the mountain rescue service GOPR in their daily activities. However it is only a part of the bigger system, which is currently being implemented. Its architecture may be found in Figure 5.

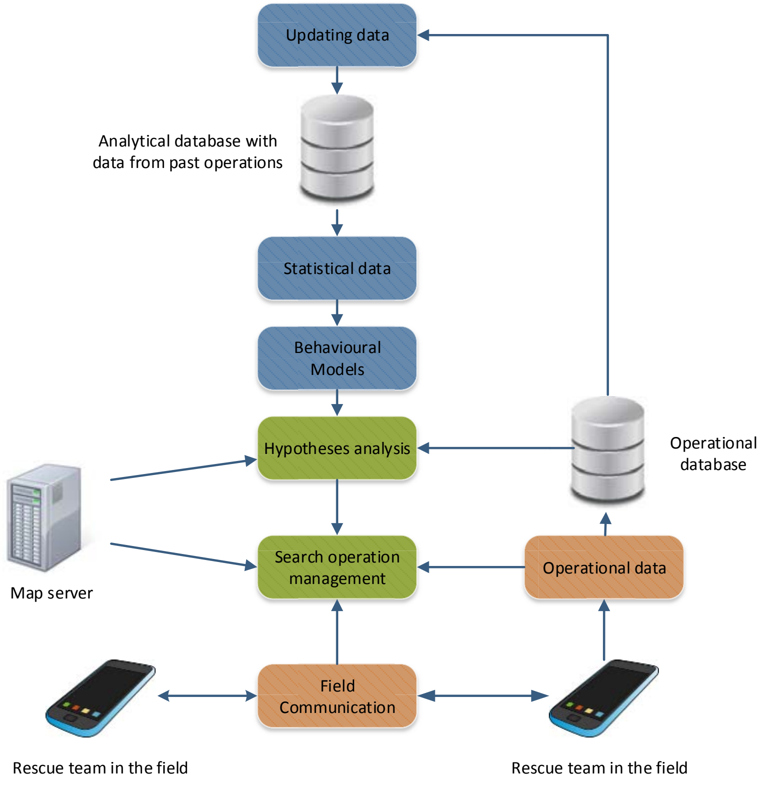

Figure 5. Planned architecture of the decision support system.

The currently used system can be found in the top part of the diagram (blue blocks). The analytical database stores the data for the models and the historical data, which is later used during hypotheses analysis.

The system consists of an automatic mechanism to archive the operational data, which is later used in both hypotheses analysis for operational purposes and in the research. The data is supplied by the elements from the bottom part like mobile devices such as mobile phones and GPS transmitters. It not only produces data which might be used for post factum analysis of the effectiveness of the action, but also allows to manage the entire operation from one central place and provides useful means for communication between the base and the rescuers. One application would be to send new information as they come in a broadcast manner to all rescuers in the field.

7. Existing solutions

Currently there are several options of GIS software, which may be used to aid SAR operations. Probably the most common one has been described in [3] and is called

MapSAR. The developers provide a stable platform to plan, maintain and execute operations. Possible functionalities include things such as resources management, printing operational data for rescuers and some basic analytical techniques. One of the downsides however is quite steep learning curve as even the simplest tasks require a lot of knowledge on how the framework operates and how the data needs to be fed to all components of the system. Another one would be, that its analytical functionalities are very limited.

Because of that, some code of MapSAR has been forked and customised in order to focus more on the analytical techniques used in SAR. The created toolkit has been called IGT4SAR and similarly to MapSAR it is distributed as an extension for the ArcGIS platform. It includes a lot of modern analytical tools not present in other frameworks such as calculating mobile phone coverage areas or watershed analysis. The presented system also strongly focuses on the analytical techniques, however it also has different functionalities and can be used to aid other aspects of SAR operation like maintaining the data and serving as a research infrastructure. It is also designed in a way to be used by an average user, that's why the extension to ArcGIS will re-implemented either as a web application on a simple desktop application. The main reason behind it, is that ArcGIS is a huge analytical application, which often overwhelms average users.

Another take on the modelling is presented in [8]. The article proposes using Bayesian networks and Markov chains [9] as means for modelling lost person behaviour. Unfortunately this idea does not have a concrete implementation and has been widely tested yet.

8. Conclusions and future work

The paper has described theoretical basis used in modelling lost person behaviour and a motivation for doing such modelling in the first place. It also describes one of the modelling methods in details, evaluates it and proposes several ways to improve it with their own preliminary evaluation. Later, a system, which is a concrete realisation of the presented modelling ideas is being introduced and described accompanied with its development plan. Some parts of the proposed system are already being used and evaluated by the polish mountain rescue service GOPR. It will be continuously developed as there is still a lot of ideas, which can help in not only the planning phase of SAR operations, but also in the information gathering and the field operation phases. In the final part of the paper existing solutions are presented with their brief description.

The preliminary results from the paper show that the improvements ideas are promising but will also require a lot of work and fine tuning of its parameters in order to get a significant result. The next step will be to evaluate the full data set and to generate at least one solution space in order to come up with a solver more adapted to the problem than evolutionary algorithms.

The system itself also needs a lot of development in order to become a highly useful tool for both aiding SAR operations and for the research purposes.

It is worth noting however that the research has only started very recently, but a lot of promising ideas has already been proposed and will be pursued.

SAR analysis methods aided with GIS are quite new and will definitely draw even more attention in the future. There is still a lot to do in that field and using decision support systems or other modern computer-aided methods and systems is only one of many possibilities. It will require a lot of cooperation between computer science specialists and SAR experts, however it is the effort, which is definitely worth taking.

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