The novel paradigm for a decision support system of the aerial non-technical survey

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Abstract: The industry of sensors and unmanned aerial systems (UAV) enables the advancement of detection of explosive objects (landmines, unexploded ordnance, improvised explosive devices) and the non-technical survey of areas contaminated by explosive threats. In the last ten years, dominates research and development of the direct detection of explosive devices versus detection of indirect indicators of the explosive threats on large areas in frame of civilian Non-Technical Survey (NTS). The impact of the mentioned phenomena is not used to its full potentials in the civilian domain of NTS. Although UAV technology can provide a large amount of data, interpretation of the data and the decision-making as an outcome of the interpretation are not developed yet. Between 1998 and 2020 many research and technology development projects on aerial NTS are realized. Some of them applied Decision Support System (DSS) paradigms: GIS-based DSS paradigm, Multi-Criteria-based DSS paradigm, Automatic Target Recognition (ATR) paradigm. The Scientific Council of HCR Center for testing, development, and training, initiated in December 2019 research and development of the Aerial Non-Technical Survey, based on UAV data acquisition, and a recommender system in its DSS functions. The proposed recommender system utilizes deep learning algorithms and collaborative filtering (CF) that rely on datasets containing selection preferences for different objects. DSS knowledge database will be based on ontologies to facilitate formal description of complex semantic structures, knowledge transfer, and reuse. The objects and preferences will be derived by fusion of features of secondary indicators, ranked by eigenvalues. The novel DSS will be implemented in the new Aerial Non-Technical Survey System which will be realized through projects by several partners. The operational validation will be done by CROMAC in mine suspected areas of Croatia.

Keywords: aerial non-technical survey, DSS, UAV, secondary mine indicators, multi-criteria ranking, deep learning, recommender system, CROMAC

Introduction

The development of Aerial Non-Technical Survey was done by many research, development, and several deployment projects, initialized in operationally validated project SMART, [1]. The Advanced Intelligence Decision Support System uses piloted helicopters and its decision support system (DSS) relies on Multi-Criteria fusion of data, information, experts' knowledge, and the secondary (indirect) indicators of explosive threats, Indicators of Mine Presence,

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Fig. 1, Fig. 2, [1]. The structure and processes in AIDSS were under continuous development and advancement and the outcomes of AIDSS become reliable and efficient, [2], [3], [4].

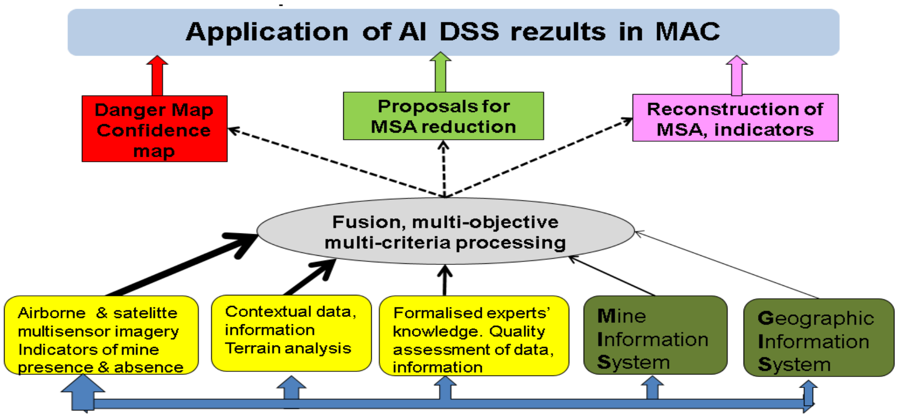

Figure 1 Advanced Intelligence Decision Support System based on Multi-Criteria fusion.

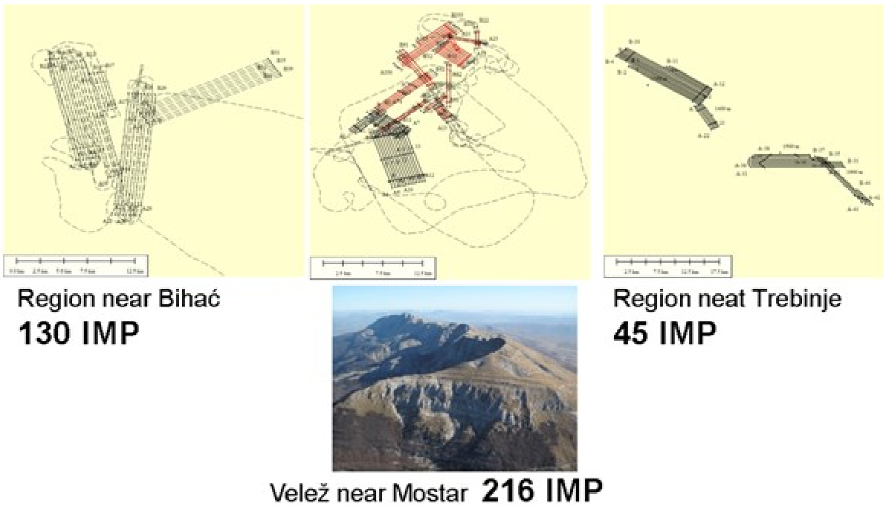

Figure 2 The helicopter flight routes, quantity of Indicators of Mine Presence (IMP) depend on terrain and situation in the former battle area. Besides the spatial data, information, the most important is experts' knowledge and contextual information and data.

Substitution of piloted helicopters with unmanned aerial systems (UAV)

The use of UAV aerial platforms instead of piloted helicopters in humanitarian mine action started approximately around the year 2010 and now UAVs dominates. One of the first applications of UAV in humanitarian mine action was in Bosnia and Herzegovina, [5]. In the last five years, the number and dimension of UAV applications are grown, mainly due to availability of the reliable industrial UAV and sensors matched for application on UAVs. Therefore the new Aerial Non-Technical Survey System shall be based on UAV with increased endurance.

Development phases of the Aerial Non-Technical Survey System

The A-NTS System developed in previous projects is planned to be upgraded in two phases, Fig 3.

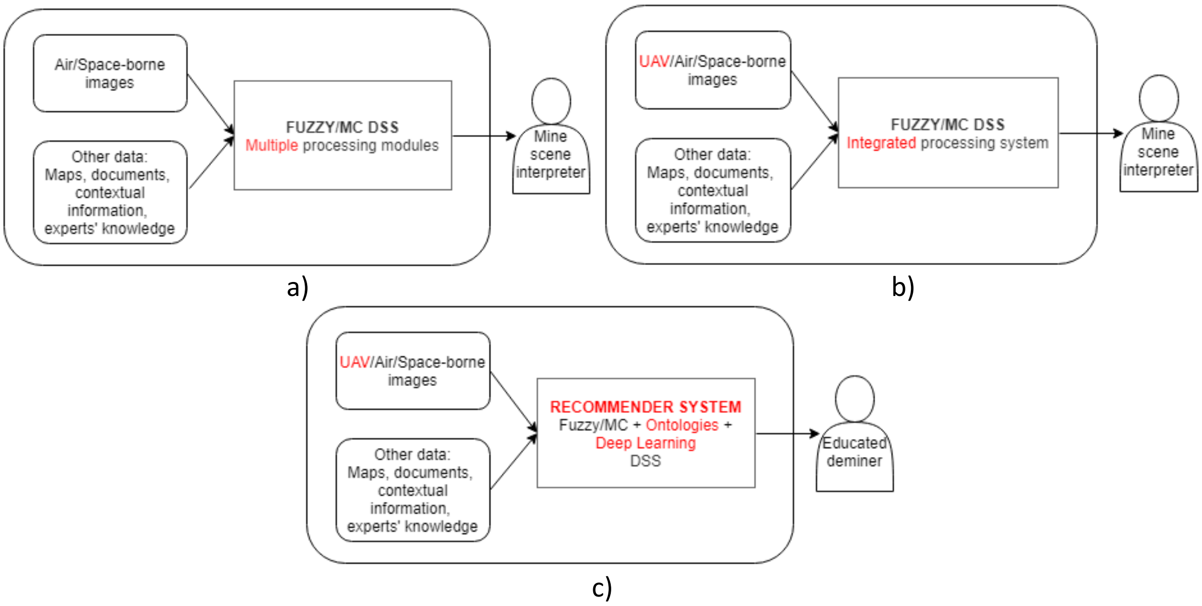

Figure 3 Development phases of the Aerial Non-Technical Survey Decision Support System / Recommender System a) Existing Fuzzy / Multi-Criteria Decision Support System (FUZZY/ MC DSS), b) Integrated DSS enhanced with UAV imagery, c) Integrated DSS extended with ontologies and deep learning.

In the first phase, multiple processing modules used by the mine scene interpreter will be integrated into one complete system. Images obtained from sensors mounted on helicopters and satellites will be complemented with UAV collected images that can be acquired on-demand and with higher resolution. The system will shorten the time of analysis and reconstruction of the mine scene, therefore, increase the productivity of interpretation and support in decision making of further demining actions in the observed explosive threats area. In the second phase implemented a recommender system based on ontologies, symbolic reasoning, and deep learning [6], [7], will enhance the usability of the system and enable its use by the educated deminer.

Ontology-based recommender expert system for non-technical survey

Computer ontologies have been successfully applied for the description of multi-level picture content, concept semantics, object labels, and relationships, especially defined in the upper levels of the picture semantics hierarchy [8] [9]. This top-down approach in document representation and retrieval has three main benefits over the opposite approach (i.e. bottom-up) which relies on media features and other low-level image descriptors. Firstly, database users prefer to articulate their search queries in a natural language, or in a constructed language similar to their preferred natural language, which is inherently capable of expression of complex semantics. Secondly, the information one can infer from raw media information cannot be automatically transformed to high-level semantics that the pictures convey. Thirdly, only rich high level full semantic representation of a picture can express the full range of relationships, explicitly observable, implicitly inferable, or with the word as a whole, the variety of supported connotations, actions, and the broader context.

The potential of ontology-based recommender systems in personalized multimedia retrieval has already been well identified [10] [11]. In this context, ontologies provide a list of suggestions presented to the user. The recommendation process considers similarities calculated between ontologies of objects and users, which reflect the descriptive features existing in the system's knowledge database. The researchers have also shown that ontology-based methods enable the interoperability of heterogeneous knowledge representations and results from inaccurate recommendations. The applicability of ontology-based recommender systems in real-life settings has been demonstrated.

However, to the best of our knowledge, the entire benefit of computer ontologies in the representation of expert knowledge for detection of explosive objects and the non-technical survey of areas contaminated by explosive threats has not been recognized and used in practice.

In this regard, we propose a novel model of ontology-based recommender expert system for non-technical survey in decision support system (DSS) functions. The knowledge base for ontological representation of relevant knowledge in the mine scene domain is shown in the next figure. The knowledge base has two main components: 1) the terminological component, and 2) the assertional component. The first component, or the terminological component (TBox), describes the relevant notions of the application domain by stating the properties of concepts and roles and their interrelations. TBox contains an ontological representation of the knowledge in mine-action technical concepts, properties, and relationships expressed in a decidable formal logic.

The second component of the knowledge base is the assertional component (ABox). It contains a formal set of assertions describing specific facts, statements, and observations in terms of terminological knowledge. ABox describes a concrete world by stating individuals and their specific properties and interrelations.

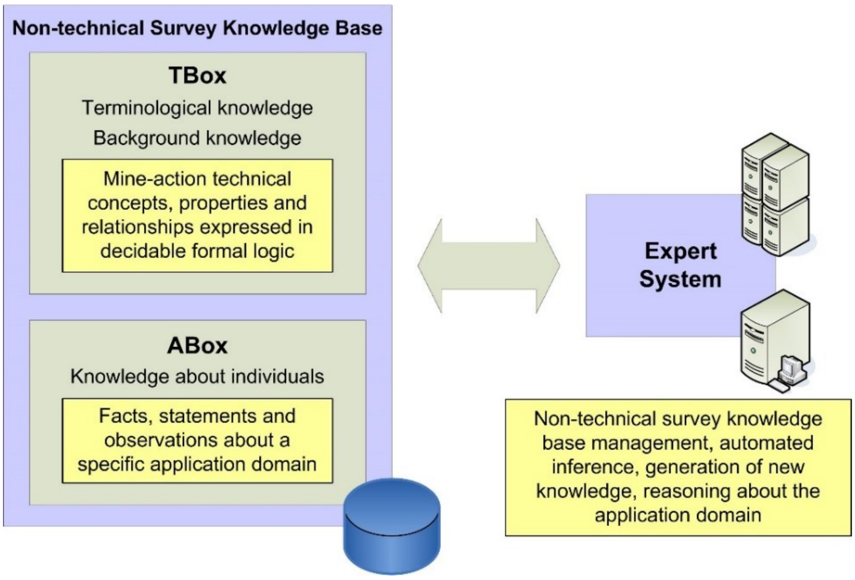

Figure 4. A schematic diagram of the Non-technical Survey Knowledge Base. The extracted information from UAV/Air/Space-born image analysis constitutes the assertional component (ABox) of the knowledge base and the terminological component (TBox) is defined by a selected foundation ontology and the developed non-technical survey mine scene interpretation ontology.

The description logic ontology language OWL 2 DL is the best choice for the construction of the Non-Technical Survey Knowledge Base because it exemplifies the optimum compromise between adequate expressivity and guaranteed decidability [12]. Most importantly for the practical implementation of the proposed system, a variety of tools for knowledge engineering are readily available which allow construction, management, reuse, and reasoning in OWL 2 DL schema [12].

The insertion of UAV/Air/Space-born images, as well as other information acquired by remote sensing in the Non-technical Survey Database, is shown in Figure 5. In this procedure, the knowledge base of the ontology-based recommender system is also being populated. Firstly, concepts in the image content that are deemed important by mine scene interpretation experts are detected and classified. After a concept is recognized, an equivalent concept must also be identified in the representation ontology. TBox must define all concepts that exist in the UAV/Air/Space-born image content. After an equivalent concept has been found a new individual is created, associated with the image, and stored in ABox. This image recognition and semantic annotation process are repeated for all images that will be stored in the proposed system.

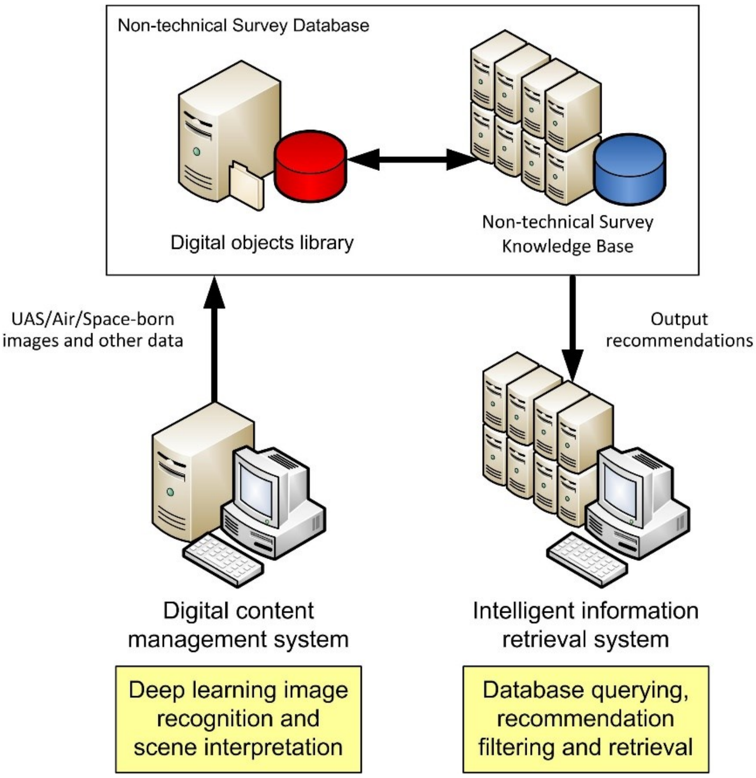

Figure 5. An illustration of the ontology-based recommender expert system structure. Input UAV/Air/Space-born images and other data are processed, for example by deep learning (DL) networks to perform image identification, classification, localization, and pixel-level instance segmentation of a mine scene. Output recommendations are generated by the expert system and the associated Non-technical Survey Knowledge Base.

As can be seen in Figure 5, in our proposal image content recognition and scene interpretation are performed automatically for example by a deep learning (DL) algorithm as an input in the ontology-based recommender expert system database. A group of mine-scene interpreters (i.e. domain experts) further inspect the picture to verify or correct the intelligent algorithm's output if required. Deep learning algorithms are a class of machine learning (ML) algorithms based on artificial neural networks with representation learning [13]. Their characteristic feature is the use of multiple layers to progressively extract higher-level features from the raw data input. From the aspect of the knowledge base, the image recognition procedure is viewed upon as a black box that yields ground truth object labels and relationships present in pictures and other input data. UAV/Air/Space-born images and other data are permanently stored in the digital objects library.

Finally, the generation of output recommendations is performed by the artificial intelligence expert system at the operator's workstation. Management of the knowledge base, automated reasoning, generation of new knowledge from the existing definitions and facts, as well as all forms of reasoning supported by the OWL 2 DL formalism about the domain of interest is executed at this workstation.

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