Prescient Profiling – AI driven Volunteer Selection within a Volunteer Notification System

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***Abstract*—A Volunteer Notification System (VNS) is a promising approach to integrate laypersons into emergency medical services (EMS). In case of a medical emergency, a VNS will alarm those potential helpers who can arrive on scene fast enough to provide the most urgent measures until the professional helpers arrive at the victim. Whereas the basic requirements and criteria of a VNS have been discussed in recent publications, this paper will focus on the actual volunteer selection process and the underlying concept of Prescient Profiling. By using concepts of artificial intelligence, the available data is processed in order to generate an abstract digital representation of a volunteer and further enhanced to produce individual user profiles. These profiles will enable predictions on future decisions and the identification of behavioral patterns within the pool of volunteers. The goal is to provide an efficient algorithm for determining a highly sophisticated set of relevant volunteers for an ongoing medical emergency.**

Keywords-Volunteer Notification System; First Responder; Emergency Medical Services; Profiling; Artificial Intelligence

I. INTRODUCTION

As stated within a recent study by the clinical center of the university Munich [1], the average arrival time for Emergency Medical Services (EMS) on scene in Germany is about nine minutes. Whereas most medical emergencies do not involve an immediate life danger for the victim, during a Sudden Cardiac Arrest (SCA) the first minutes are of utter importance. The probability of permanent brain damage increases with every minute and a time interval of more than five minutes without treatment will most likely result in the death of the victim [2][3]. The severity of the time deficit generally correlates with the infrastructure a country can provide, resulting in intensification for less advanced countries.

One possible approach to provide the most urgent medical measures before the professional EMS arrive on scene is the implementation of a Volunteer Notification System (VNS) as discussed in [4]. The basic concept of a VNS is the integration of laymen and medical trained volunteers into the EMS by notifying those potential helpers who are, at the time of incident, “close” to the victim. Whereas the term “close” is suitable for describing the general idea, the actual process of selecting the relevant volunteers within an ongoing medical emergency requires, due to possible obstacles as e.g., rivers, traffic jams, or alternative transportation means, a sophisticated algorithm in order to ensure the best possible set of potential volunteers at any given time. Artificial intelligence (AI) offers a variety of methods in the area of problem solving [5] and for implementing self-learning systems [6] aiming to increase the quality of decisions by adaption over time. The possibilities of AI driven system within the scope of a VNS will be introduced within this paper.

The remainder of this paper is organized as follows. The difference between a simple and an intelligent volunteer selection will be discussed in Section II, whereas Section III will highlight the necessity of an intelligent approach by describing some non-trivial decision scenarios in which simple selection algorithms will provide flawed or inaccurate results. Section IV will therefor introduce the basic concept of (prescient) profiling within this domain as a suitable approach to enable an AI driven volunteer selection. Further research perspectives are discussed in Section V.

II. VOLUNTEER SELECTION

In case of an incoming emergency call, the responsible dispatcher will alert the professional EMS and – in case a cardiac arrest or any type of emergency that requires immediate treatment is suspected – trigger the forwarding of the information into the notification system [4]. The VNS will now decide which volunteers are to be alarmed. In order to prevent unnecessary notifications – hence, notifications that will immediately appear irrelevant to its recipient or notifications alarming volunteers without any plausible chance of reaching the victim in time – an efficient selection algorithm is required [7]. This algorithm has to forecast the approximate arrival time of an individual volunteer at the scene of the incident.

A. Simple Volunteer Selection

A simple solution for selecting volunteers is the implementation of a notification radius, defining a maximum distance around the place of incident and alarming those volunteers who are within this radius. This approach will provide a set of helpers who are geographically close to the victim, but will they also arrive on scene faster than potential helpers outside the notification radius? To forecast an individual arrival time, more information is required on both,

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the volunteer and the environmental details affecting her at the moment.

B. Intelligent Volunteer Selection

Whilst the actual distance is an important parameter to be considered when deciding if a volunteer should be notified or not, it does not necessarily determine the volunteers' time of arrival at the scene. Due to impassable obstacles (e.g., highways or rivers), the beeline calculation does not offer a suitable background for estimating the arrival time, but even the consideration of up to date map material – like so enabling a shortest way calculation – will not provide sufficient information without additional assumptions.

Thus, the type of movement, the physical performance of a volunteer and the current traffic situation, all have a direct influence on the approximate traveling time and thereby on the time of arrival. Furthermore, limiting the relevant decision parameters to merely distance or traveling time appears inadequate and secondary criteria apply; e.g., the potential volunteers' medical expertise, her individual knowledge of the area and the current situation this volunteer is involved in. An efficient algorithm hence has to consider a broad variety of available information on each individual volunteer in order to generate a reliable set of potential helpers [7][8].

III. SCENARIOS

The necessity of an intelligent volunteer selection is demonstrated by multiple non-trivial decision scenarios, as illustrated in Fig. 1. The place of incident is close to a railway station (the red bar located on the railway tracks). Leaving heuristics aside, implying to have only five volunteers in total, the most promising of these are to be notified. The use of a simple volunteer selection – as introduced in Section II – will result in the following set of volunteers (as marked within the red area) that will be alarmed:

- the pedestrian just north of the incident,
- the volunteer in the car (on the highway), and
- the pedestrian in the park (close to the river).

An intelligent volunteer selection will demand further information on each potential candidate than just her current location. The following section gives a short discussion on each single volunteer and the required additional information to decide reliable if the volunteer should be notified or not:

1) *The pedestrian just north of the incident* is geographically the closest volunteer. A straight road connection and no obvious obstacles result in minimal requirements on travel speed or physical performance. This candidate appears a solid choice no matter further assumptions, but eventual circumstances could prevent her from arriving in time, e.g. she might be traveling with her children which she picked up a few minutes ago; just like she does every day at this hour.

2) *The volunteer in the car* is the second closest, but should she be alarmed? Depending on the direction the car

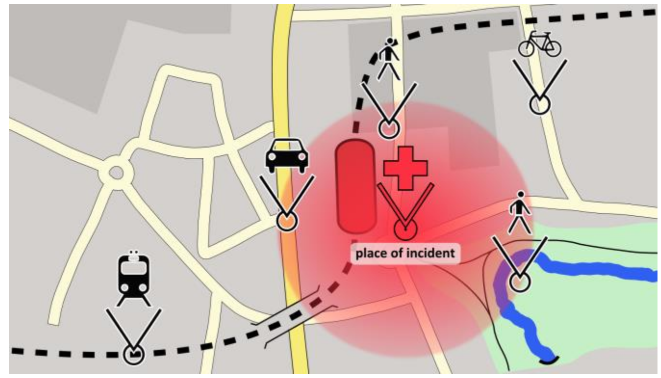

Figure 1: Non-trivial volunteer selection

is driving and the distance to the next highway exit, this volunteer will most likely have no option to arrive on scene in time.

3) *The pedestrian in the park* is blocked by a river. This volunteer will only arrive in time when the next bridge is within reach. Furthermore, with the park being a green zone with limited map material available, it might only have a single exit that is far away.

4) *The volunteer riding the bicycle* is outside the notification radius, but due to traveling speed and possible short-cuts, she might arrive on scene fast. Parameters like one-way roads or uphill/downhill will influence the arrival time but generally she appears a good choice for notification and compared to a car with the same distance, she will not require a parking place and isn't slowed down by high traffic (which occurs more often around stations).

5) *The last volunteer (in the train)* appears to be far away, but assuming that the train rides in the right direction and will also stop at the next railway station, she might arrive on scene earlier than any of the other volunteers.

Within the illustrated scenarios, the notification radius resulted in a set of three volunteers, from which probably only one has a realistic chance to arrive at the victim in time. Moreover, potentially highly valuable volunteers have not been considered for notification. The given examples are just a small selection of possible scenarios in which no simple answer on if to alarm a specific volunteer exists.

In order to determine the best possible set of volunteers for an ongoing medical emergency, an efficient selection algorithm is required which postulates the availability of a complex knowledge base. A variety of parameters is to be collected, processed and evaluated, forming the digital profile of an individual volunteer.

IV. PROFILING

The term profiling has been frequently used over the last years in different research areas. Within the field of information and computer science it is mainly used in conjunction with the terms: program behavior [9][10], (web) user [11][12], network [13], or social media [14].

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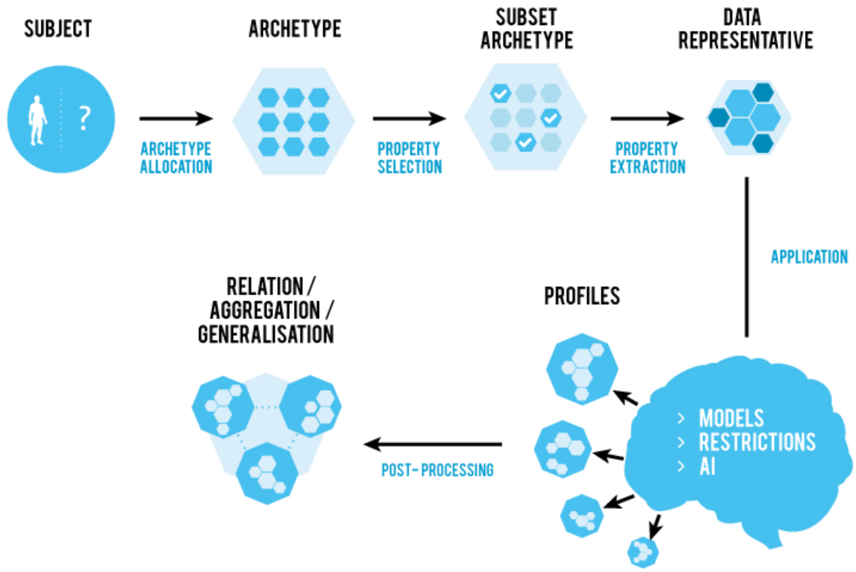

Figure 2: Sub-processes of Profiling

A. General usage

Generally, profiling is defined as "the act or process of learning information about someone based on what is already known" [15]. This definition is vague concerning the act or process used to obtain information and does neither define the kind of information retrieved nor its origin. Due to this lack of an exact definition, an appropriate assignment of methods, techniques or technologies regarding profiling is not possible without clearly distinguishing between the various implementations and their individual context.

In order to specifically define the process of profiling that will be introduced within this paper, it is necessary to present a definition of what profiling describes within the scope of an intelligent volunteer selection in correspondence to aspects of information and computer science. Furthermore, the requirements and outputs that are to be expected by the application of profiling have to be defined.

The term profiling is hereby not to be confused with a profile. A profile is commonly defined as "a brief written description that provides information about someone or something" whereas the verb to profile is defined as the action "to give a brief description […]" [15]. This definition defines a profile as the result of a process generated to describe someone or something, i.e., an abstract representation of the profiled subject.

B. Definition

Profiling describes the process of generating profiles from obtained data, associated to one or multiple subjects. A profile itself is a non-empty, finite, ordered tuple with a positive number of elements. Each of these elements consists of a finite number of values corresponding to its individual domain. The process of profiling is divided in multiple sub-processes, which are illustrated in Fig. 2. The various terms describing these sub-processes and the different artifacts which are their results, are shortly described as follows:

1) Subject: A subject describes "what" is actually being profiled. Within the VNS, the subject will be a registered user (a human being) but in general, anything can be profiled; e.g., a life-form, medical symptoms or an abstract stream of data. This definition stays in correspondance to the term subject as reffered to in [16].

2) Archetype Allocation: Due to the generic background of the profiled subjects, the system needs an approximate "idea" of what kind of subject it will deal with. The archetype allocation describes the process of mapping a subject to a specific archetype.

3) Archetype: The archetype is an abstract representation of anything that can possibly be profiled. It defines the maximum set of properties that are available on a specific subject. Archetypes can consist of other archetypes as elements; e.g., a human can have a car or children as elements in the archetype, whereas children are themselves represented as humans within this set.

4) Property Selection: After a subject has been mapped to an archetype (or a combination of archtypes), it has to be decided which of the available properties are of importance for the profiling process. While it is theoretically useful to support algorithmic selection and re-adjustments in this selection process by implementing a suitable learning strategy, a simplified approach will only process the property selection once, i.e., the properties representing the subject are not modified during the profiling process.

5) Subset Archetype: After the relevant properties have been selected from the archetype, the structure of the digital representation of the profiled subject is determined. This artifact is referred to as subset archetype and constitutes the base of the following data representation.

6) Property Extraction: The property extraction describes the process of collecting the data (e.g., trough available sensors or automated systems). The selected properties of the subset archetype will be filled with values. This process will result in the creation of the data representative.

7) Data Representative: The data representative conforms to the abstracted, digitalized description of a subject. It consists of the selected properties of its subset archetype and holds the raw data from occurred property extractions. This term is not the same as a data subject introduced in [16] but instead differentiates due to its raw data characteristic.

8) Application: This process is defined by the application of different models, processing the data representative . The processing will lead to a profile of the data representative. Possible models are introduced in the upcoming section.

9) Profile: A profile is a generalized representation of the data representative. The degree and direction of the generalization is defined by the context of the profiling process, i.e. the applied models.

10) Post-Processing: This step describes the generic approach of applying various methods to the existing profiles. Examples are clustering, association analyzes, or the identification of relations between profiles.

11) Relation/ Aggregation/ Generalisation: This artifact describes the result of the post-processing. Examples for this category are sets of profiles which are aggregated by associations or relations between them, or group profiles representing identified group properties.

C. Application models

In the context of behavioral predication, application models are generally based on theoretical rational behavior [17], bounded rationality (i.e., psychological models) [18], or on models that are based on observations which are characterized by methods of machine learning algorithms [19]. Beside the sole implementation of a single approach, a combinatorial aggregation of different types of models is possible. Recent research states that especially the use of hybrid models which are based on machine learning, but add features from psychological models, performed significantly better in various domains [20]. An alternative process is the sequential application of different models to a single data representative in order to retrieve specific properties of that profile.

D. Prescient Profiling

With the data representative uniting the digitalized properties of a subject that were collected over time, a base for further processing is available. Applying different models (as discussed above) will result in individual profiles that enable various operations; e.g., clustering and the evaluation regarding specific criteria. This process conforms to the definition of profiling as given in Section IV, while prescient profiling may be considered “the next step” on top of this basic definition, using the profile(s) to generate new insights and therefore enable enhanced capabilities.

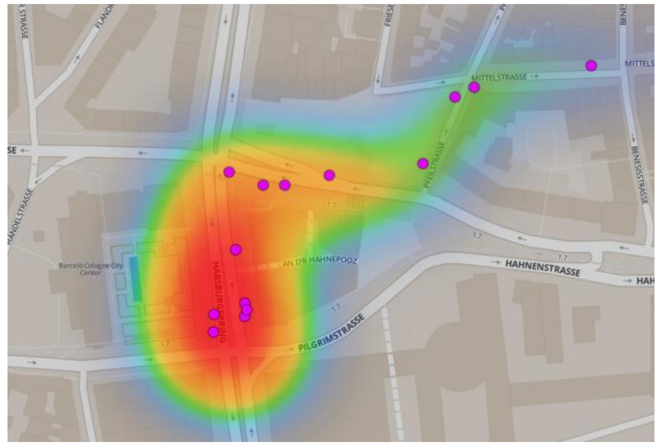

Figure 3: Location heat map

Implying a learning system approach, thus, a system that uses methods of AI to learn from past observations and thereby identifies trends and patterns, will not be limited to analyzing the historical values but instead will have the ability to make predictions. This states an enhanced definition of profiling. The term “Prescient Profiling” therefor refers to this special type of profiling, aiming to make reliable predictions on both, the value of individual properties and on a profile itself.

E. Profiling within the VNS

In the context of a VNS, the subject of profiling will be the volunteer (i.e., the registered user). The corresponding archetype is human with the following, exemplary properties to select from: gender, height, weight, age, location, number of children, type of car. Within the property selection, only the location is selected as property that is filled with data during the property extraction process. This extraction will occur automatically, i.e., the mobile phone will continuously push updated information on the volunteer’s location to the VNS server. All incoming location updates are stored in the data representative of this volunteer and applying specific models will generate different types of profiles. One suitable approach is the generation of a so called heat map [21] as part of the resulting profile. This location heat map, as illustrated in Fig. 3, describes the current whereabouts of the volunteer to be profiled as probabilities, rather than a single valid location; the calculation is based on the available location data from within the data representative (i.e., the purple dots).

By generating profiles of different volunteers and applying post-processing methods, e.g., clustering or pattern recognition, aggregated profiles are being created, representing the relation between different volunteers and their corresponding heat maps. In addition, trends and progresses in the development of individual heat maps can

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be analyzed in order to create group profiles or enable various predications.

V. Conclusion And Outlook

Whereas a basic VNS implementation is able to notify volunteers in the closer vicinity by using simple selection algorithms, various scenarios have been discussed in which an efficient volunteer selection will require the consideration of additional factors. The concept of profiling has been introduced as a suitable solution within this context, aiming to generate profiles of individual volunteers. This is achieved by creating a data representation of the profiled subject, based on specific parameters that are selected from an archetype definition within the property selection and filled with data during the property extraction process. The application of different types of models, integrating various concepts of pattern recognition and machine learning in order to identify behavioral patterns and coherences between volunteers and individual properties, describes an enhanced process of profiling that has been introduced as “Prescient Profiling”, utilizing the various profiles to enable predictions on individual subjects or groups.

The research focus of the near future will be the actual implementation of the machine learning approach and the development of corresponding models. The explicit application of Prescient Profiling within the context of the VNS needs to be analyzed, developed and evaluated. With an integration of the VNS system into the emergency workflow of regional EMS partners planned for the beginning of 2014, promising possibilities for an efficient data assessment are being created; enabling benchmarks and comparisons of various selection models in different emergency scenarios and thereby producing academic results on the efficiency of an AI approach for volunteer selection in medical emergencies.

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References

[1] Study of the Institute of Emergency Medical Care and Medical Management (INM) in Munich, “Untersuchung zum Notarztdienst und arztbegleitenden Patiententransport in Bayern“, Published by the clinical center of the university Munich, April 2010.

[2] J. Bahr, “Lay resuscitation in the German rescue system. Some basic information”, volume 10, issue 3, Notfall Rett. Med. 2007, doi:10.1007/s10049-007-0910-y, pp 197-200.

[3] K. Grassl, “Herzdruckmassage im Rahmen der Laienreanimation: Einsatz eines audiovisuellen Echtzeit-Rückmeldesystems“. Dissertation, LMU Munich: Faculty of Medicine, 2009.

[4] J. Elsner, M.-T. Schneiders, M. Haberstroh, D. Schilberg, and S. Jeschke, “An Introduction to a Transnational Volunteer Notification System Providing Cardiopulmonary Resuscitation for Victims Suffering a Sudden Cardiac Arrest”, In: Proceedings of the Fifth International Conference on eHealth. IARIA, Nice (France) 2013, pp. 59-64.

[5] S. Russel, P. Norvig, “Artificial Intelligence: A Modern Approach”, Third Edition, Prentice Hall Series in Artificial Intelligence, Pearson Education 2010.

[6] C. M. Bishop, “Pattern Recognition and Machine Learning (Information Science and Statistics)”, Second Edition, Springer Science 2007.

[7] J. Elsner, M.-T. Schneiders, D. Schilberg, and S. Jeschke, “Determination of Relevant First Aiders within a Volunteer Notification System“, In: Proceedings of the International eHealth, Telemedicine and Health ICT Forum for Educational, Networking and Business (Med@Tel 2013). Med@Tel, Luxembourg 2013, pp. 245-249.

[8] J. Elsner, P. Meisen, S. Thelen, D. Schilberg, and S. Jeschke, “EMuRgency – A Basic Concept for an AI Driven Volunteer Notification System for Integrating Laypersons into Emergency Medical Services”, unpublished..

[9] D. W. Wall, "Predicting program behavior using real or estimated profiles", In: Proceedings of the ACM SIGPLAN 1991 conference on Programming language design and implementation, Toronto, Ontario, Canada, ACM, 1991, pp. 59-70.

[10] T. Ball, J. R. Larus, "Optimally Profiling and Tracing Programs", ACM Transactions on Programming Languages and Systems, volume 16, 1994, pp. 59-70.

[11] P. K. Chan, "A non-invasive learning approach to building web user profiles", In: WEBKDD'99, Workshop on Web Usage Analysis and User Profiling, San Diego, CA, USA, 1999.

[12] M. Pazzani, D. Billsus, "Learning and Revising User Profiles: The Identification of Interesting Web Sites", Machine Learning, volume 27, issue 3, June 1997, p. 313–331.

[13] K. Xu, Z.-l. Zhang, and S. Bhattacharyya, "Profiling internet backbone traffic: Behavior models and applications", In: Proceedings of SIGCOMM 2005, conference on Applications, technologies, architectures, and protocols for computer communications, volume 35, issue 4, 2005, pp. 169-180.

[14] R. Li, S. Wang, and K. C.-C. Chang, "Multiple Location Profiling for Users and Relationships from Social Network and Content", In: Proceedings of the VLDB Endowment (PVLDB), volume 5, issue 11, 2012, pp. 1603-1614.

[15] www.merriam-webster.com, Online dictionary, Keywords: profiling / profile, Available at: http://www.merriam-webster.com/dictionary/ [Accessed: 08. October 2013].

[16] M. Hildebrandt, S. Gutwirth (Eds.), “Profiling the European Citizen: Cross-disciplinary perspectives”, Springer Science 2008.

[17] N. Giocoli, “Modeling Rational Agents: From Interwar Economics to Early Modern Game Theory”, Edward Elgar Pub 2003.

[18] R. Lin, S. Kraus, J. Wilkenfeld, and J. Barry, “Negotiating with bounded rational agents in environments with incomplete information using an automated agent.”, In: Articial Intelligence, volume 172, issues 6-7, April 2008, pp. 823-851.

[19] K. P. Murphy, “The Machine Learning: A Probabilistic Perspective”, MIT Press 2012.

[20] A. Rosenfeld, I. Zuckerman, A. Azaria, and S. Kraus, “Combining Psychological Models with Machine Learning to Better Predict People's Decisions”, In: Synthese, volume 189 issue 1 supplement, Springer Science 2012, pp. 81-93.

[21] L. Wilkinson, M. Friendly, “The History of the Cluster Heat Map”, The American Statistician 2009, volume 63, issue 2, pp. 179-184.