The Windmill Method for Setting up Support for Resolving SparseIncidents in Communication Networks (Extended Abstract)

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***Abstract*— This paper introduces the Windmill method for constructing situation sensitive communication support systems for organizations consisting of a network of autonomous professionals involved in standard duties encountering occasional incidents of a time-critical nature for which they have to call for help. The Windmill method is based on statistical data filtering techniques for ranking incidents and available communication resources among which human personnel according to their expected frequency, availability, location, skills and experience. It is especially useful for domains in which the human workforce changes over time and incidents are relatively sparse with respect to location and frequency of occurrence.**

communication networks; recommender technology; incident management; Professional Task Setting with Incidents; instance-based learning

I. INTRODUCTION

In domains such as security & surveillance, traffic & transport, medical care and the military, hundreds of professionals are spread over a network consisting of various groups across different organizations to perform various standard tasks at different places and move from one location to another over time. Such tasks are by nature urgent, local, incident prone and require the deployment of resources in terms of personnel, materials, and infrastructure. These tasks often interfere with and depend on each other, as performing these tasks typically involves the activities and knowledge of other people at other locations, thus leading to non-local emergent effects. For ease of reference we will call such a setting a Professional Task Setting with Incidents, PTSI for short.

PTSI is not the same as general crisis/incident management. PTSI concerns frequent disruptions of routine tasks by relatively small incidents, whereas crisis management and incident management during crises deals with large and disastrous events [12]. Such disasters often entail a collapse of key infrastructures. In addition, crises occur less frequently than PTSI related incidents However, organizations specializing in PTSI are typically called in to help in crisis management situations.

Incidents threaten the performance of both individuals and the organization as a whole. Handling contingencies requires the right knowledge to be exchanged and rescheduling or canceling planned activities. For instance, security firms in the private sector offer their clients surveillance services as a way to protect property from theft and vandalism. As a deterrent, surveillance routes are scheduled by these firms such that the different premises are frequently visited [13]. The surveillants, however, have to cancel or delay their schedule intermittently to respond to incoming alarms elsewhere or to assist one of their colleagues in need of help [5].

In particular, situation assessment, coordination and task assignment to members of different organizations is vital to satisfy the intra- and inter-organizational goals given those interdependencies. Especially, when individuals are not co-located, information and communication technology should be called upon to coordinate the actions aimed at handling incidents.

Incident management in PTSI needs to be effective at all stages without requiring an unsupportable overhead in communication and processing amongst people and data sources. In crisis situations this management is often severely obstructed by lack of adequate information about the availability, whereabouts and expertise/quality of resources. For example, typically a central communication point (e.g., a regional dispatch center), which is deployed to deal with unexpected events, classifies incoming incidents and propagates them as a request across organizations to find proper assistance. During crisis situations such a central communication point may become a bottleneck or single point of failure. Furthermore, it may lack the information to send the request, including the relevant event data, to the proper group of people.

One of the aims in general incident management and in PTSI is to reduce the time needed in the different phases: preparedness, prevention, detection time, communication time, travel time and clearance time and recovery [11],[7]. The motivation for this paper is to improve communication with respect to the response times and resolve times in PTSI and to advance the research on automated Incident Management Systems (IMS) **Error! Reference source not found.** by offering a method for embedding machine learning and data mining techniques to manage communication networks.

We introduce the Windmill method that supports the development of communication support systems for incident management in PTSI. Windmill specializes in developing systems that create situational awareness in domains where knowledge retention is typically low, due to personnel changes, and the sparseness of incidents with respect to time and location.

The remainder of this paper is organized as follows. First, we present a problem analysis of incident management in PTSI domains. Next, the Windmill method is introduced and formalized in the fourth section to develop a sufficient set of communication support algorithms to handle incidents efficiently and effectively. In the last section, we briefly discuss the contribution of our work, as well as intended extensions of our work and that of others.

II. Problem Analysis

An incident is defined as "an occurrence or event, natural or human-caused, that requires an emergency response to protect life or property" [12]. Incident management in general depends heavily on communication between all parties involved for coordination, task allocation, resource allocation, and information sharing; this is also true for incident management in PTSI.

For use throughout this article, we define the following typical concepts in PTSI. Typically there is a set of actors A representing the professionals comprising mobile professionals P, team-leaders TL and operators D of a central communication point (i.e., a dispatch center). Together actors are responsible for a set of tasks, denoted by $\mathcal{T}$. The tasks are divided over a set S of work shifts on a corresponding set R of routes such that a set of objects O is visited sequentially on each route. In order to resolve incidents of type $I \subseteq \mathcal{T}$ (e.g., a burglar alarm in a mobile security setting) starting at time-point t at object $o \in O$, the actors engage in communication meetings (i.e., calls and telephone conferences). Each meeting $m \in M$ starts at time-point t_{start} and ends at a time point t_{end} and is associated with an expected incident management performance in terms of, for example, the response time (including the expected travel time from one object o_1 to the incident location o_2). Meetings can be ranked by their expected performance. Such incident-specific and context-dependent (e.g., the incident object) communication meetings result in a change of shifts S, consisting of *planned, active* and *finished shifts*.

The dispatch centers are used for the coordination of activities in PTSI. As a consequence, during incident management these centers are likely to form a communication bottleneck, with the risk of a single point of failure (see Fig. 1). Important for such centers is the span of control they have, i.e., the number of people that a single supervisor can successfully manage and coordinate from such a center. The span of control can be increased if each incident takes less time to handle; especially, if the "easy" incidents can be handled without intervention (only monitoring) of the dispatch centre.

In PTSI the main body of personnel is mobile; moving from one task to the next, often in predefined routes, else in response to a range of incoming tasks. As a result, if an incident occurs, those with experience for such an incident might not be on the scene. This spatio-temporal character of PTSI makes it hard to determine whom to call to handle the incident.

Another complication for some PTSIs is that personnel changes relatively quickly, either taking different positions in the organization, or leaving the organization altogether. As a result, knowledge retention in the human part of the organization is low. To some extent, this also holds for PTSIs in which people work in shifts; the best person to deal with a particular incident might not be at work at all, and may be not available for communication.

A final aspect of incidents in PTSI is the spatio-temporal sparseness of incidents. Although the frequency of the different types of incidents is high, the occurrence of these incidents over time and space is sparse. As a consequence not every employee has experience with all incidents in all locations.

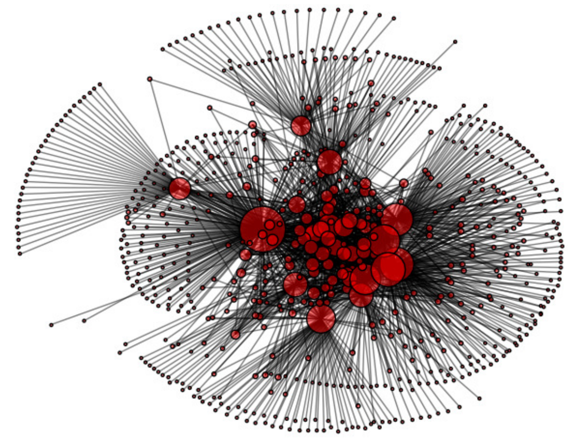

Figure 1. Communication network of actors in MHS security. Larger vertices are dispatch operators and team leader. Smaller vertices are guards.

Currently, situational awareness of those that operate a communication point, such as dispatch center, is only supported by providing data and information on whereabouts of the personnel, key performance indicators concerning their activities and actual spatio-temporal information on the unexpected events at hand [8]. For most of the time, operators still have to rely on their own situational awareness to decide who to call. They cannot reliably predict who has the most relevant expertise and who is near the incident. This results in ineffective delegations of tasks causing an overall incident management delay.

In professional PTSI organizations, information on personnel, other organizations, the ICT infrastructure, application usage and performance is stored in a continuously updated (centralized or distributed) database. However, some knowledge in such organizations is distributed over the personnel and is exclusively available through communication.

III. Windmill Approach

We developed the Windmill approach by mapping the difficulties and the opportunities of problems with a time-critical component to a set of aspects (each hierarchically ordered), such that locally available knowledge is applied immediately (being the top ranked knowledge in all aspects). For the example, in mobile human surveillance security surveillance, the aspects involve the location of the incident; spatio-temporal availability of personnel; the expertise of personnel; expected travel time of selected personnel to the location of the incident; and feedback and performance. If that does not supply a solution, statistical learning, and activity spreading is used progressively over the hierarchy to more and more general but still grounded knowledge.

The Windmill concept is based on the idea that the set of aspects corresponds to the set of blades on a windmill, see Fig. 2. Per blade/aspect, the knowledge available is hierarchically ordered according to its relevance. The centre of the mill, where all the blades meet at the axis, represents the most relevant instance corresponding to a particular incident, which actually denotes the core of the problem by the most detailed description available. Moving up the blades, to the outside, the position on the blades corresponds to knowledge that is decreasingly relevant to the specific instance and can be considered to be more general. The fantail of the windmill (that which keeps it directed to the wind) represents the defined performance criteria set for estimating and evaluating the performance of potential communication. The milling itself stands for the performance of these potential communication connections; the fasters the milling, the better the performance. The adaptability with respect to different time-scales and generality of information is represented in the blades of the windmill.

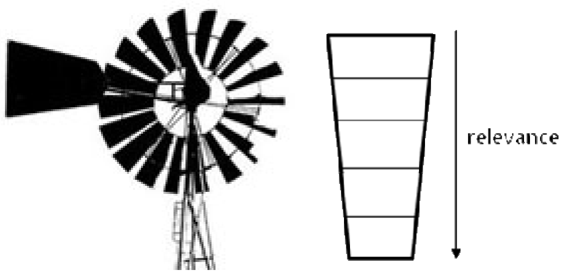

Figure 2. Windmill & a Blade in more detail

For PTSI our mapping to blades of the Windmill is as follows: Because of the time-critical nature and the spatio-temporal character of the incidents, the best solution is a local one, meaning that the PDA of the professional on scene uses information stored in the PDA to recommend a solution. Also, information available from on-site information sources, for instance, from an alarm console, can be incorporated in the recommendation process.

For PTSI, the main aspects relate to the characterization of the incident in terms of the location of the incident; the availability of personnel (including spatio-temporal attributes); the expertise of personnel; expected travel time of selected personnel to the incident; and feedback (implicit and explicit).

Degradation overtime of the expertise of personnel is taken into account. That is, if someone once was an expert in handling an incident of a certain type, and that professional has not handled such an incident in a long time, than that person is no longer considered an expert for that type of incident. The degradation speed is modelled in Section IV.

The Windmill approach exploits the opportunities of PTSI: the latently existing knowledge in databases and the knowledge distributed over the personnel of the organization. The databases are used to bootstrap the system, and for occasional re-bootstrapping the system. The distributed knowledge is used in two ways: the system uses explicit feedback by the personnel to improve its recommendations, and by contacting the PDA's of personnel in reach. Finally, implicit feedback is obtained about the adequacy of the recommendations by evaluating the way the incident was handled, as well as by evaluating overall performance of the system. Overall evaluation is essential, since local actions, can have non-local effects, in worst case a cascade of other incidents.

In such a way a communication support system can be developed that extracts this knowledge and makes it available in the form of situation-sensitive recommendations of whom to contact given an incident. By incorporating a communication set-up system, see [10], the communication lines to the recommended employees can be set up automatically and the employees can be provided with the proper situation- and incident-specific information. After the incident, the actors are asked to provide feedback on the quality of the incident support. Learning and spreading the induced communication activity patterns will show that significant improvements in the quality of assignment actors to incidents can be achieved.

IV. COMMUNICATION SUPPORT

In this section, we define our Windmill approach for the problem of recommending communication by introducing the basic elements of the PTSI. We show how each solutions to an incident can be associated with an estimated performance measure. Also, we discuss and tackle the issue of sparseness and spatio-temporal dynamics arising when estimation is performed while taking into account the context and spatio-temporal characteristic related to the incident and possible solutions.

A. *Communication Elements in PTSI*

Our Windmill approach is on the one hand based on the personalization of the recommendation of communication networks – this personalization is achieved by empirically modeling a so-called feedback rating function.

On the other hand our approach is based on applying solutions fitting to new incidents that occur using implicit key performance indicators. Past communication activities are analyzed in terms of the original incident I that *caused* this communication, the available group configurations that were eventually contacted and the circumstances in which this took place.

Using the Windmill approach requires logged data for analysis and bootstrapping purposes. These logged data should include the performance of past solutions to incident and task handling, each associated with the communication session instigating the solution, the nature of the incident itself and the spatio-temporal context in which the solution was achieved. We define such collections of logged data by a set L consisting of a finite number of events. Each event e

is represented by a tuple (*a, g, τ, c, t*) where the components, $a \in A$, $g \in G$, $\tau \in \mathcal{T}$, $c \in C$ and $t \in T$, denote the following:

- *A* is a set of actors in charge of a task,
- *G* is a set of groups having participated in incident related communication, strictly $G=2^A$,
- $\mathcal{T}$ is a set of tasks including incidents in set *I,*
- *C* is a power set of context elements, and
- *T* is a set of time points.

The goal of communication support is to find a suitable group *g* for a specific actor *a,* that is working on at task τ, such as an incident $i \in I$, while taking into account the context *c* and the time *t* at which this takes place.

B. *Performance Estimation*

To determine the usefulness of suggested solutions to handle an incident, we introduce the concept of a performance measure indicating to which extent the requirements for incident management in PTSI where met. Subsequently, we discuss the estimation of performance candidate solutions. Estimation is needed, because the performance function is only partially known.

1) *Performance of Incident Solutions*

Each incident or task handled by an actor $a \in A$ can be associated with a performance measures established afterwards. The performance *v* associated with each event is given below by Function 1.

$$v\colon A \times G \times \mathcal{T} \times C \times T \rightarrow \square \tag{1}$$

Usually function *v* is normalized on a range between 0 and 1: higher values still correspond with more desirable outcomes and lower values do to less desirable outcomes.

The performance function comprises measurement of, for instance, the operational performance (e.g., response times) individual judgments (i.e., ratings) or the workload. The precise definition of the performance is dependent on the actual application domain. For instance, if arrival times are paramount for some PTSI organization, then this is reflected in the logged data storing the performance measurements.

Performance can only be measured after the incident has been handled. Incidents that occur in a new or unique context do not have an off-the-shelf solution. Therefore, an estimation function is introduced.

2) *Performance of Incident Solutions*

Given an incident *i* for which actor *a* is responsible at time point t concerning context *c,* the goal of recommending communication is to find a group g of actors to set up a meeting between a and g, such that the expected performance resulting from that meeting is maximized using a mapping h: $A \times \mathcal{T} \times C \times T \rightarrow$ G:

$$h(a,i,c,t) = \arg\max_{g\in G}\left(\hat{v}(a,g,i,c,t)\right), \tag{2}$$

where a ∈ A, g ∈ G, i ∈ I, c ∈ C and t ∈ T. While *L* may contain a large set of events, it is unlikely that for any incident a ready and fitting solution (i.e., a group $g \in G$) can simply be retrieved from *L* that concerns the same actors and context. Therefore, the performance for these new events *e'* has to be estimated using the events in *L*. Estimating performance is done by a function *v***.**

For estimating the performance of potential solutions, and as such constructing recommendation schemes that fit new incidents occurring, the Windmill approach allows comparing new events to past events. This is achieved by an estimation function for *v* that weights past solutions by their relevance using a relevance function δ and aggregates the associated performances according to its weights, see Equation 3.

$$\hat{v}(e,\sigma^n) = \frac{\sum_{e'\in L} v(e') \times \delta(e,e',\sigma^n)}{\sum_{e'\in L} \left|\delta(e,e',\sigma^n)\right|}, \tag{3}$$

where each *e* and *e'* consists of a tuple (*a, g, τ, c, t*) and σ^n is a set of *n* scale parameters to allow, for instance, non-linear weighing of the relevance metrics. Here *n* corresponds to the amount of elements in the tuple *e* = (*a, g, τ, c, t*). While applying the windmill to communication support, *n* is 5.

Although such context-sensitive incident information can be used to select the right recommendation schemes, these incidents may be sparsely distributed over time and space making those schemes become unreliable, i.e., the recommendations schemes will be based on too few cases to guarantee certain accuracy. Furthermore, changes over time *t* will make those solutions obsolete. In the next sections, we will further detail function δ and address these issues of sparseness and dynamicity.

C. *Data Sparseness*

In practice only a part of the logged data is relevant for estimating the performance of new events. A very trivial, but effective way of diminishing the amount of data to process is to discard all events older than some time point t_0. On the other hand too little information causes data sparseness to grow to undesirable levels, resulting in inaccurate estimation of the performance of recommended communication.

Although discarding data seems effective as a way to deal with abundance, this does not solve problems of *the curse of dimensionality*. Reducing the amount of dimensions (e.g., contextual information) can alleviate the estimation process. That is, while any contextual element in *C* can be included in the estimation process, narrowing the number of aspects reduces the amount of computational effort needed to estimate the expected performance of potential solutions to a new event.

The Windmill approach focuses on establishing a hierarchy of past events, associated solutions and their performance in terms of the relevance to a fresh incident occurring. To determine the relevance of each past events, each aspect can be weighted separately such that the relevance function of a pair of events is defined as the product of the relevance of all its pair members. This is defined in Equation 4.

$$\delta(e, e', \sigma^n) = \prod_{i=0}^{n} \delta(e_i, e'_i, \sigma_i) \tag{4}$$

Here, the relevance of an event *e* to a new event *e'* is determined by the product of each member of those events being, for instance, an actor, the communication group, the actual incident or task, the context and the time of occurrence. Each of the relevance metrics can be weighted according to some weight σ_i corresponding with the scale size for that particular type of aspect. (see section D) The data instrinsic scale σ_i can be learned by iteratively validating the function $\hat{V}$ against a set of training data.

By allowing each aspect to contribute to the estimation of the candidate solution's performance independently of the exact composition of elements, also events that have never occurred in reality can be assigned an expected performance based on strong correlations between the different observables. For instance, if we assume that actors a_1, a_2, a_3 visited object o_1 and, also, that actors a_1 *and* a_2 visited object o_2, *u*sing some correlation as relevance measure, (i.e., a_1 and a_2 performances at o_1 and o_2 show some correlations), we can propagate the performance of a_3's visit to o_1 to estimate a_3 performance at o_2 using the relevance together with the scale σ_i.

D. Spatio-Temporal Dynamics

In order to arrive at grounded relevance measures (i.e., similarities) the Windmill approach proposes to aggregate and to distribute of the logged performance measurements. It proposes to continuously do this dependent on the measured properties of the incidents and the observed contexts, among which those of alternative communication groups, such as response times and experience in relation to incidents.

1) Statistical Learning

The Windmill approach embraces statistical learning techniques [15], correlation-based filtering approaches such as collaborative filtering(viz., [2] and [6]) and link-prediction techniques (viz., [3] and [9]). Those techniques are in particular useful in capitalizing on the statistical similarities and the changes therein amongst the preference and performance schemes of actors *a* with respect to another group of actors *g* over incident space *I*, context space *C* and time domain *T*.

Learning is finding a function $\hat{V}$ that minimizes the error between V and $\hat{V}$ for all log events in *L* by adjusting the weights or even by altering the relevance metrics used (e.g., by using a evolutionary algorithm). The learning can be applied both in an on-line and off-line fashion.

The relevance measures determined can be calculated in advance. Stored relevance schemes can be updated regularly in the *background* and for each element a top *k* list of most relevant *neighbors* can be kept. By repetitively applying expectation maximization on the events with respect to their performance, we retain primal incident-specific and contextual personalized hierarchies of ordered communication support schemes for the particular application domain:

$$\{(a,\tau,c,t), h(a,\tau,c,t), \hat{v}(a,g,\tau,c,t), v(a,g,\tau,c,t)\} \tag{5}$$

These schemes identify for all new incidents a number of possible groups to communicate with, an estimated performance and, if available, the real performance as determined after resolving the incidents. Note that such a recommendation scheme hierarchy is still dynamic over incident and context classes and at larger time-scales, and that it may even evolve.

2) Activation Spreading

To enhance the estimation of the performance of incident solutions under the temporal dynamics and changes in other aspects, we propose an activation spreading approach with respect to the relevance measure between new and past events [4]. The spreading of the performance data across potential regions of (a, g, τ, c, t) space has to be corroborated by grounded similarity measures between the individual elements or classes of that space. For example, incidents may fall in a similar class allowing aggregation, weighing, normalizing and ranking of the performance data as in previous section.

However, how and to which extent this data concerning individual space elements or segments is exchanged and combined is not a trivial thing. Especially the fact that this data becomes obsolete makes it a cumbersome task for people to assess new situations.

In order to resolve these problems, the Windmill approach drives on a data-driven technique in which the spreading function is governed by an equation generating a so-called scale-space, viz.[14], of the performance function, that is:

$$\Pi : v(A \times G \times I \times C \times T) \rightarrow \underline{\hat{v}}(A \times G \times I \times C \times T \times \Sigma) \tag{6}$$

For example, some security objects are visited by particular guards more often than other guards. These guards are therefore more acquainted with these objects. The experience of an actor *a,* in dealing with a particular type of incident *I* with respect to a particular security object *c*, is time-dependent. This experience is associated a given decay factor or typical temporal scale of alarm handling performance. Together with the other aspects all this can be expressed in terms of a scaled performance function $\underline{\hat{V}}$. This scaled function takes into account the multi-set of scales $\Sigma=(\sigma_1,\ldots, \sigma_n)$ for the different event types. The relevance measure associated with $\underline{\hat{v}}$ can be defined as follows:

$$\delta(<a,g,\tau,c,t>,<a',g',\tau',c',t'>,\sigma_1,\mathrm{K},\sigma_5) = \\ \delta(a,a',\sigma_1)\times\delta(g,g',\sigma_2)\times\delta(\tau,\tau',\sigma_3)\times\delta(c,c',\sigma_4)\times 2^{(t'-t)/\sigma_5} \quad (7)$$

in which *t'* is a starting time and $\delta^{a,g,\tau,c,t}: F \times F \rightarrow [0,1]$; $F = A \square G \square \mathcal{T} \square C \square T$ are relevance functions between different instances (i.e., observable) of one PTSI aspect. In order to measure the degree of correspondence between these observables, a Kendall correlation is calculated for each pair within the same class by ordering the guards by visiting frequencies to a particular location weighted by the recentness of the visit, viz.[5].

Note that the space F is a topological space with a non-Euclidean or rather affine metric. The space and time aspects might be associated with, for instance, a Minkowski metric, but the performance function can also be induced using other non-Euclidean relevance or similarity metrics. This entails that the activation spreading process – eventually node and link creation - ensures that those observed performance measurements for pairs of events are aggregated that are most similar. The scale parameter determines to which extent similar events will influence each other and therewith will resolve sparseness or even incompleteness.

V. Discussion

The Windmill method enables the development of incident-specific and context-sensitive personalized communication support systems for incident management organizations faced with uncertain, rare, dynamic and time-critical incidents. It embraces agent modeling, statistical learning and activation spreading techniques using appropriate scale-space theories for analyzing the dynamic communication network topology over time induced by appropriate performance measures.

We aim to integrate the communication system presented in this paper in the normal procedures of day to day surveillance work, indeed first-responders. It will as such not suffer from sparseness, contextual and volatility issues [5]. Furthermore, we aim to further explore the relationship between multi-agent system emergency operations and emergency planning and plans, in which local MAS operations would be more appropriate than using centralized IMSs.

Concerning the statistical learning and activation spreading methods in this paper we employed classical scale-space methods in order to quantify and predict missing links in communication networks. In order to capture and propagate the asymmetry in the connectivity and preference relations amongst actors and nonlinearity in the communication network dynamics and evolution, we will study and report in upcoming articles on the performance function and associated data-consistent scale-space governing equations.

Last but not least, we aim to apply our Windmill method to other problems, such as knowledge management support across organizations or creating socially intelligent ICT support networks for, for instance, the elderly.

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