MODELING RFID TRACKING IN HEALTHCARE

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ABSTRACT

This paper presents the modeling and simulation of patient tracking in a hospital emergency department (ED) using radio frequency identification (RFID) as would be typical in a real time location system (RTLS). These types of 'smart' applications typically extend the role of traditional RFID while leveraging existing RFID infrastructure.

Keywords: *RTLS, locating, tracking, monitoring, emergency department, agent based modeling, contact graph generation.*

INTRODUCTION

While there continues to be an increasing range and variety of radio frequency identification (RFID) applications and devices prototyped and implemented in healthcare settings, much less work has been done on modeling RFID systems in healthcare [1]. In order to gain insights into implementation parameters of RFID applications, this paper presents a use case which investigates the modeling of smart RFID in healthcare related to smart hospitals. Relying on an RFID deployment – primarily for patient tracking in an emergency department (ED), with a particular interest in person-person contact graph generation, the nature and extent of uncertainty and error in the system can be investigated. One can use this evaluation to assess how well an RFID system translates to real installations and real data.

The intelligence or 'smart' aspect of the application is in the range and objectives of follow-on analysis of data collected. Once personal contact graphs are generated, a number of semi-analytical tools can be used for graph analysis. For instance, an explicit interest is to apply infection spread models to contact graph data, and gain insights into how infection may spread through an institution or facility. This is inherently relevant to hospitals, but can also be a part of other organizations' pandemic preparedness strategies.

SMART PLATFORMS IN HEALTHCARE: DEPLOYMENT AND MODELING ON RFID INFRASTRUCTURES

Beyond its traditional applications in static inventory control, a proximity based RFID system augmented for personal tracking [2] is an excellent candidate for use in on-line data collection and to generate person-person contact graphs (graphs of personal social networks). A considerable number of RFID systems have been researched and deployed in organizations and healthcare facilities utilizing a variety of technologies and methodologies [3]. For instance, Real Time Location Systems (RTLS) using RFID can be combined with time-sequence detection and correlation to develop cost effective patient/staff safety models for use in the ED [4]. Some deployments combine RFID with the benefits of pervasive and context-aware computing [5] to further enhance patient safety and healthcare personnel interoperability [6]. As such, existing RFID infrastructures in a clinical setting can be leveraged to collect data to estimate personal contact graphs, which become inputs to backend analysis tools (e.g., automated 'anomalous' patient status/condition and/or behaviour determination; and, infection spread modelers and simulators). In this work, a 'smart' ED is modeled using an agent based model (ABM). ABM allows the modeling of individuals such as patients, healthcare workers (HCWs), and equipment when the system is modified to include tracking and monitoring [7]. The purpose of the ABM is to emulate the operations of a typical ED. Patients arrive by various means, are triaged and registered, and are treated. In most EDs, this process is interspersed with waiting times [8]. Waiting times include queues at triage, queues in waiting areas, and queues in consults or diagnostic services [9]. These are also typically prioritized by triage score and potentially modified by cumulative waiting times.

In the scenario of an ED equipped with an RFID system, the ED will be provisioned with a number of RFID readers and a backend system capable of logging RFID tag 'reads,' their location (reader proximity), and time of day (time stamp). RFID readers provisioned among a real-world ED floorplan are as illustrated by circles in Fig. 1.

Figure 1: ED layout provisioned with passive RFID Readers; circles indicate a read range, radius ≈ 2m

An RFID system typically is composed of tags and readers. The readers are either passive (inexpensive) or active (more expensive, but with greater read range). These are proximity systems that nonetheless carry considerable uncertainty associated with estimates of exact locations. In this work, we model passive RFID readers with a maximum read range of approximately 2m, consistent with the GAO GP-90 passive reader using clamshell RFID tags. The advantage of this type of system is that the tags are very inexpensive and could reasonably be provisioned to all pieces of medical equipment as well as patients, allowing for considerable tag loss as patients leave with their tag (elopers) or in the event that the tags are disposable (non-recyclable).

Fig. 2 represents a closer observation of a patient in a treatment area, in which the red circle indicates a tag reading. In this model, the RFID readers backhaul their read data – wirelessly, or otherwise – to a database where contact data is stored and contact graphs may be generated from the data. An immediate advantage of an RFID-based data collection method for contact graph generation is that the system leverages existing RFID infrastructure, and existing clinical grade networks supporting wireless connectivity, adding value to an institution's original RFID investment that was not otherwise considered.

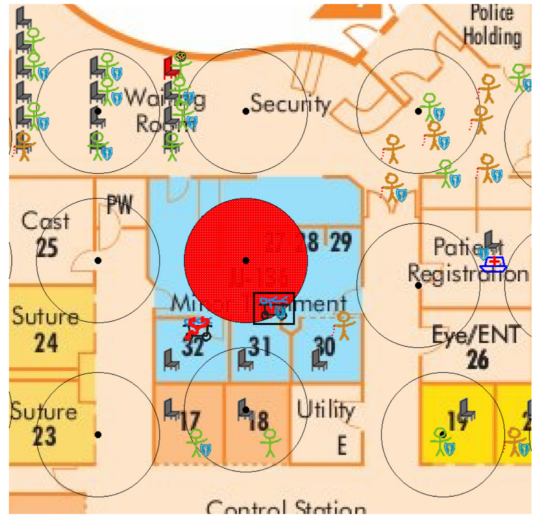

Figure 2: A snapshot of patient 'triggering' a tag read

A further advantage of the RFID proximity system for contact graph generation is the system's inherent collection of spatial as well as temporal object data. This is a direct result of knowing the position of readers within the ED.

DISCUSSION

In the case of the RFID model for data collection, an ED was simulated using an agent based model with various staffing resources of nurses, doctors and patients, with log files created for various patient arrival rate scenarios. Data collected includes reader IDs, tags IDs 'read', and the read times. One difficulty (reflecting a real-world deployment) is associated with estimates of location, as the reading process is fairly stochastic and somewhat unpredictable [10]. An assumption was made that the individual remained in close proximity of a given reader until read by a subsequent reader. The greatest insight came from estimating an individual's positional (spatial) error as they traversed the ED. These difficulties and observations made it possible to model a near-ideal reader configuration such that errors in position could be mitigated while estimates of personal contact improved. It should be noted though that the spatial error in the contact graphs are considerable when compared with exact (simulated) positions known within the ABM. There is no immediate fix to the proximity estimation errors, but algorithms such as a Kalman filter could readily be employed to improve the degree of uncertainty associated with these types of RFID infrastructures [11]. Notwithstanding the difficulties associated with uncertainty of proximity information extracted from an RFID system, the model was run to emulate 'extraction' of contact graph information.

The model was revised to improve its ability to reflect a person's contact network from monitoring explicit interactions. In this case, the ED is modeled with all individuals being equipped with RFID tags. Assuming a degree of power control, a read range roughly corresponding to approximately 1.5 meters was used as a reader's capture cross-section. A contact graph was then built from the data extracted over a day's simulation of roughly 100 patients and is illustrated in Fig. 3.

Fig. 3 illustrates the degree of connectivity between HCWs (physicians and nurses) as well as patients. The graphs illustrate a) the visualization of the raw connectivity uniformly distributed over a unit circle; and b), the graph drawn after placement using a simulated annealing algorithm, attempting to minimize edge length. The edge weight is the accumulated period when two agents are within the same read range of a RFID reader.

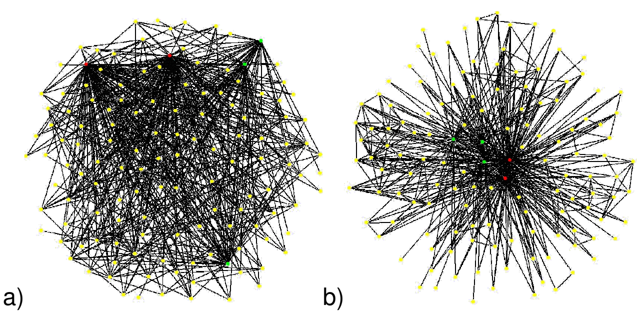

Figure 3: A contact graph collected from the modeled RFID-RTLS (via ABM), a) random placement, b) placed after simulated annealing

An objective of the work was to create a visual representation of the contact graph data that was both visually appealing as well as intuitively informative. After experimenting with grid placement as well as uniform circular placement, uniform rectangular placement was selected as best achieving these objectives once node clustering was undertaken. As with uniform circular placement, the nodes are uniformly distributed in space. The color scheme in Figs. 3 represents different HCWs and patients: Doctor – red; Nurse – blue; Patients – green (low), yellow (medium), teal (high), for various (triage) levels.

Ordering the placement using traditional visualization techniques was based on *simulated annealing* algorithms. The fitness functions of interest were in improving the display, as opposed to minimizing graph area or edge crossovers. Operations such as node swapping were used and probabilistically accepted in minimizing edge weight or cost. Fig. 4 illustrates the distribution for the corresponding contact graph, relating the relative number of edges to nodes (100 persons) histogram.

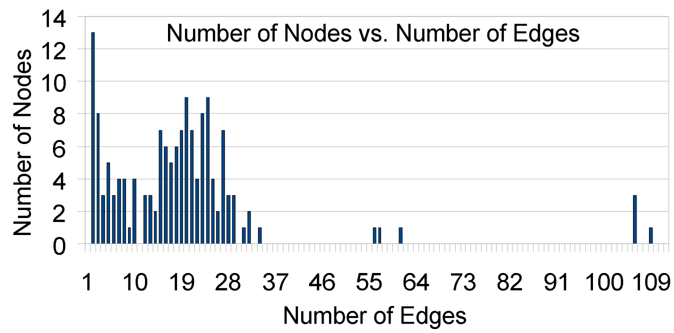

Figure 4: Contact graph – distribution

Similarly to placement, post-processing included a node clustering phase whereby nodes are permitted to move as well as being swapped. The clustering algorithm was originally written using a 'greedy approach,' but was later changed to a simulated annealing approach to achieve an accompanying small improvement in overall graph fitness. A representative graph placement is illustrated in Fig. 5.

Data generated for Fig. 3 through 5 are associated with a model with minimal uncertainty. In effect, the RFID technology modeled allowed estimations of proximity or contact without error. An error model associated with RFID patient tracking has been fully discussed in [12]. It is anticipated that improved RFID-based RTLS in the future will provide increased levels of fidelity, such as those modeled above, whereby the degree of uncertainty can be reduced.

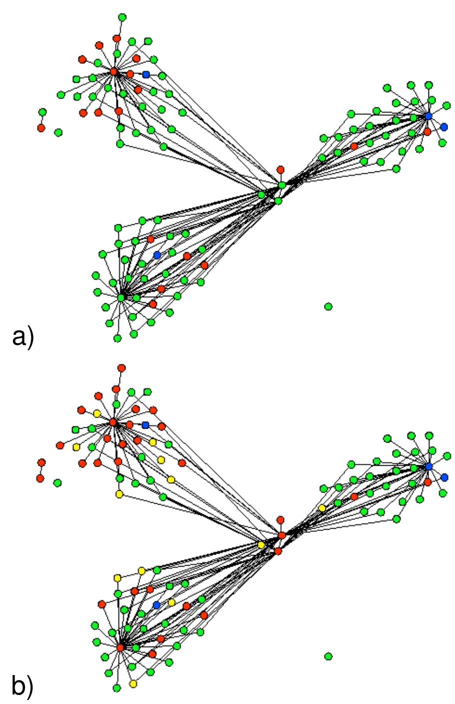

Figure 5: Filtered contact graph placed and clustered, illustrated with a filtering of the lighter weight edges: a) before infection spread, b) after infection spread.

The techniques outlined are a viable means of collecting contact data with various degrees of probabilistic interpretation required. One final aspect associated with the automated means of contact data collection is that contact with inanimate objects can also be collected and analyzed. For example, handwashing stations can easily be equipped with similar wireless devices (RFID readers) to monitor compliance with hygiene protocols. Once a contact graph has been produced, a number of analysis methods can be used to estimate infection spread and model possible intervention policies [13]. Such algorithmic detection schemes can also be implemented on the same contact graph to ensure that other essential medical compliance policies and practices are adhered to (e.g., 'five rights of medication safety,' and avoiding patient neglect).

Although the generation and organization of the contact graph can be an end in itself, a potential follow-on objective of this work is to apply a mathematical disease spread model on the contact graph data. An SIR mathematical model or variant is a good first candidate. The Susceptible, Exposed, Infectious, and Recovered (SEIR) variant is exemplary of a simple mathematical model that represents the health state of an individual by a stochastic process [14]. Using contact graphs, one can undertake models of infection spread within a population with a more realistic 'model of contraction' based on the extent and duration of contacts based on each individual. Fig. 5 a) and b) illustrate the stochastic progression of an infection based on an SEIR individual disease spread model resulting from contact duration. Here red illustrates the 'infected state' of an individual within the contact graph and the time evolution (from a) to b)) of the infection spread illustrates the progression of the infection.

SUMMARY

This paper presents the modeling of a novel means by collecting person-to-person contact data leveraging an exiting RFID system within a smart healthcare facility. The utility of the contact graph information would be within an individual-based model to provide insight into how infection spread may be influenced through face-to-face contact within a specific facility. Individual-based predictive disease spread models are stochastic processes with transitions influenced by the degree of contact people have with one another. The RFID method of data collection represents a data collection means whereby contact data can be obtained as a byproduct of the normal operation of the facility's RFID infrastructure. As specific sectors move toward implementing tracking systems to assess organizational efficiencies, the data collection of a person's contacts could be automated. As any error introduced in the data collection process is largely a consequence of the inherent uncertainty due to RFID reader positioning and radio signaling, it should be recognized that the data is at best statistical and should therefore be evaluated within that context.

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