Modeling and Architecture of Mobile Computing Systems

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Abstract. *A Pervasive Computing system has to deal with the contextual information (context), which characterizes the current situation of the involved entities (e.g., users, mobile devices). There are different scientific fields studying the various problems that may arise, depending on the aspect from which they are observed. This thesis studies issues related to the capability of a pervasive system on adapting its behavior to the involved entities context / situation. Specifically, the interaction between the user and such system has to be less intruding as long as the latter recognizes the current user situation and adapts its functions accordingly. Hence, the human intervention is kept to a minimum since such system is designed to bother the user as little as possible. The thesis focuses on context knowledge representation and management as well as on algorithmic issues related to contextual information dissemination. Such issues comprise the concept of Context Awareness. Problems that have been studied include context representation, interpretation, sensing, discovery and inference along with the capacity of a system to reason about context and perform certain (pre)defined tasks in advance. Through approximate reasoning (Fuzzy Sets Theory), bio-mimetic dissemination algorithms (Epidemical Spreading) and the appropriate derived algorithms the aforementioned problems have been modeled and studied. Consequently, in this thesis, the semantic enhancement of context, context fusion / inference, context adaptation, collaborative context awareness and context discovery issues have been clearly shown.*

Key words: Pervasive computing, context awareness, approximate reasoning, epidemical algorithms.

1 Dissertation Summary

1.1 Context and Situation Awareness

In the recent years we have witnessed rapid progress in the pervasive computing paradigm. Pervasive computing is emerging as the future computing paradigm in which infrastructure and services are seamlessly available anywhere and anytime. This paradigm is the result of recent research and technological advances

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in wireless and sensors networks, distributed systems, mobile computing, autonomic and context-aware computing. In order to render a *Context-Aware Application* (CAA) intelligent enough to support contemporary users everywhere / anytime and materialize the so-called *ambient intelligence*, information on the present *context* of the user has to be captured and processed appropriately. Context may refer to the user's position, physical properties (e.g., temperature) or other general parameters (e.g., the specific devices that the user carries). The efficient management of *contextual information* requires detailed and thorough modeling along with specific processing and inference capabilities.

Diverse pieces of context can appear (e.g., user is in her office, walking outdoor, driving a car) in which different user activities can be performed (e.g., attending a meeting, taking a break). A well-known definition of context is referred in [1], [9]: *context is any information that can be used to characterize the situation of an entity. An entity is a person, place or object that is considered relevant to the integration between a user and an application, including the user and the application themselves* [10]. *Context - Awareness* (CA) is the ability of a computing device to sense, interpret, and interact with aspects of a user's environment. A *context-aware application* (CAA) has to be able to determine that the user is involved in different situations at different times.

Situation - Awareness (SA) is considered as the particular kind of CA, where *situation* is viewed as logically aggregated pieces of context as proposed in [2], [3], [4] . SA is not restricted on location awareness, which means that a mere determination of a geographical location and knowledge about that location is only provided. The combination of sensor data with spatial knowledge leads to a detailed representation of the environment, i.e., the current user situation. Situations are based on user activities in specific locations. The interaction between the user and the mobile device would be made easier and less intruding, if the latter recognized the current user situation and adapted its functions accordingly. The human intervention must be kept to a minimum since a CAA should be designed to bother the user as little as possible. Devices that know more about the user context are able to function efficiently and transparently adapt to the current user situation, leading to the idea of the *invisible computer*. The device autonomously learns and automatically suggests what actions the user prefers in designated situations. This is a challenge, since a device should react intelligently to everyday social situations [5].

The efficient extraction, fusion [13] and determination of relevant pieces of context from diverse sources are a key issue in SA. *SA is an abstraction that exists within our minds, describing phenomena that we observe in humans performing work in a rich and usually dynamic environment.* The problem of handling possibly imperfect observations from multiple sources includes the problems of information fusion and multiple sensor data fusion. However, such vague information may lead to inexact context reasoning [7], [11]. Specifically, vague context implies vague situation estimation and, thus, approximate reasoning over situations and actions. Approximate reasoning is a critical process in situational computing because of (*i*) the lack of computational resources, (*ii*) the need for time-critical decision-making, and (*iii*) the possible lack of relevant training data. The different kinds of imperfection can be handled through the frameworks of the Fuzzy Set Theory and the Possibility Theory. However, the Fuzzy Logic (FL) –an algebra on Fuzzy Sets– is appropriate for real-time decision-making allowing a degree of uncertainty at the context estimation and decision making phase. FL principles express human expert knowledge and facilitate the automated interpretation of the estimation results. Allowing a degree of fuzziness not only at the user situation estimation aspect but also at decision making (e.g., triggering of actuation rules) makes a CAA more robust, flexible and capable of handling user reactions.

1.2 Collaborative Context Awareness

In our everyday life, we frequently experience cases where persons group together (e.g., in museums, university classes). Typically, such persons share (at least temporarily) common interests and preferences (e.g., group of persons interested in the same exhibition or painting). *Group members* experience similar situations and many of their mobile computing devices (*nodes*) sense and process *identical* contextual information. The described setting, which is not so rare, introduces the need for treating CA in a collaborative manner. *Collaboration* denotes the *synergy* between the nodes of group members (*neighbors*) for sensing, interpreting and sharing contextual information (e.g., node A misses a certain contextual input which is captured and sent by node B, node C interprets contextual input that is disseminated by node D).

Important definitions related to collaborative context awareness are the following: *Collaborative Context-Awareness* (CCA) implies the understanding of the context of others that, consequently, provides a more enhanced context for an individual as proposed in [14], [8]. Collaboration among nodes improves context quality by providing a primary context approximation for further refinement at each node. *Collaborative context* is the *context* acquired through (*proximity*) networking between sensors and higher-level devices and can be used to increase the common understanding about the surroundings, improve context availability and context reliability (through the acquisition of additional / supplementary context from neighbors). A Collaborative Context-Aware System (CCAS) comprises a group of nodes capable of sensing, fusing, inferring and intercommunicating in order to achieve common or similar context. The CCA framework yields robust CA applications, i.e., immune to transient sensor failures or contextual information disturbances. Moreover, significant economies of scale can be achieved, i.e., not all nodes need to carry the same, overlapping set of sensors or expensive, fault resistant components. Missing or erroneous contextual data is *substituted* by other nodes, thus, leading to truly dependable applications. Overall, the benefits stemming from the introduction of CCA remind us the Belgian motto *L' union fait la force*, denoting that, unity makes strength. A CCA application relies on information dissemination algorithms for context sharing. In this article, we propose a scheme for disseminating and, collaboratively, determining *context* and *inferred context* within a CCAS. The proposed scheme derives from an epidemiological model. We found great similarities between the epidemiological model and the internals of a CCAS, mostly in the abstractions of virus spreading, virus severity, virus interdependencies and possible trasmutations [12].

1.3 Prior Work

The idea of learning a system to adapt to future user intentions and reactions, and deal with imprecise knoweldge and decision making in SA is quite novel. Several situation models describe context by a set of roles / relations in a low-level ontology [6] and infer the invovled situation of an entity. However, such models do not adopt a learning scheme in order to adapt to the reactions of a user, do not take into consideration imprecise sensor readings and do not perform adaptation according to the user's feedback. Moreover, dealing with a CCAS, several approaches have been proposed to model and simulate mono-epidemical spreading in networks. In [15] the authors analyze a Markov process-based framework that characterizes the spreading of epidemics through the SIS model and the impact of the underlying topology on propagation.However, the concept of *transmutation* of an epidemic is not considered since there is no semantic processing (i.e., context inference and reasoning). The authors in [16] investigate the threshold of a mono-epidemical propagation exploiting the eigenvalue of the adjacency matrix of the network. Our model generalizes the model in [16] investigating the behavior of each epidemic, thus, in case of a mono-epidemical propagation our results coincide with those in [16]. To the best of our knowledge, there is no other application of epidemiological models to CCAS. Our model goes beyond a simple epidemiological model and introduces the abstraction of stronger and transmuted epidemics. The prior work however has not incorporated the concept of aggravation and transmutation.

2 Results and Discussion

Due to space limitations, in this section we only present a bio-mimetic approach of disseminating contextual information in a CCAS. Context refers to the current values of specific parameters that represent a node's activity (e.g., walking), event (attending a lecture), environmental information (e.g., illumination) in a specific place and time. *Inferred context* is the additional information that can be deduced from the current sensed / determined context. In a CCAS, the *epidemic* represents a piece of context (e.g., illumination measurement) or inferred context (e.g., attendance of lecture) that is *valid* for a certain period of time and/or within a specific location (e.g., for a certain number of hops). A group of nodes can share and exchange context, thus, forming the collaborative context for that group. Nodes incapable of inferring (*new*) context can acquire such knowledge once context transmutation takes place: if a collaborating node in a group has the ability to infer context then it can disseminate it into the group, thus, augmenting the current common knowledge, i.e., the collaborative context for that group.

This *reciprocity* guarantees a *modus operandi* for a network of *autonomous* nodes working under the model for collaboratively sensing, determining, sharing and, inferring context.

Epidemiological models assume that individuals go through a series of states at a certain set of rates. In the *Susceptible-Infected-Susceptible* (SIS) epidemiological model, infectious individuals are those that have contracted the epidemic and can infect the remaining susceptible ones. After a period of time, infected nodes may recover from the epidemic and then transit to the *Susceptible* state. In that state, they can get infected again, thus, in the limit, any individual constantly switches between the two states: *Susceptible – Infected*. Therefore, the SIS model assumes that, a node in the *Infected* state cannot be re-infected by another *stronger* epidemic. We extend the SIS model at that point, i.e., an infected node can be re-infected with an epidemic through transmutation resulting to the *aggravation* of the node's condition; the node is more infectious and it may infect neighboring nodes with context or inferred context (see Figure 1). On the other hand, the cure of an infectious node refers to the *improvement* of its condition. The abstraction of cure indicates that context is no longer valid (e.g., contextual information is either obsolete or beyond the scope of the CAA application). We call the extended biomimetic model *Susceptible – a-Infected – Susceptible* (S*a*IS), where *a* stands for *a*ggravation. The S*a*IS model is, essentially,

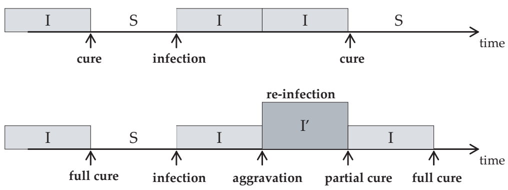

Fig. 1. The state transitions of the SIS and the proposed S*a*IS model. A possible transmutation of an epidemic may result in the aggravation of the condition of a certain node.

an epidemic algorithm but unlike previous schemes for broadcast (e.g., Flooding), the model deals with numerous dependent pieces of context, referred to as multi-epidemical propagation. Each piece of context is regarded as a different epidemic and transmuted epidemics may spread in the network simultaneously. The strongest epidemic has the potential to infect a large portion of susceptible nodes, contrary to weaker epidemics, which infect a small portion of the group. The proposed model is *scalable* w.r.t. the possible number of transmutations. In the long run, portions of the population are infected with epidemical transmutations. It should be noted that, in the S*a*IS model transmutations are assumed to circulate in the network. This is totally different from the fact that several *independent* epidemics (i.e., with no semantic relations among them) co-exist in a network, as shown in the selective epidemical information dissemination.

The semantic relations among epidemics are exploited by the involved nodes to substitute, or complete, or infer *new* context.

2.1 Context Representation

The representation of context in each node poses a significant challenge. Modeling context is complicated due to the fact that different nodes *value* differently their pieces of contextual information. Especially, in a CCAS, different types of context might appear, for instance, the context of each node in a group (*individual context*), the context of the group itself (*collaborative context*) and the context of the task. Specifically, the context determined by a *sender* node might be differently viewed / interpreted by the *recipient* node. This means that, the collaborative context ϕ, which is collaboratively deduced by a group of nodes, does not necessarily imply that all nodes of that group assume individually identical context. Instead, the context p for every node can be at least as specific as ϕ notated as $p \succ \phi$. This reaffirms the selectivity attribute of the SaIS model, in which, each node obtains the precise information it requires. Nevertheless, each node can, further, locally refine contextual information independently of other nodes. A hierarchical knowledge representation scheme is adopted for context. The dependency $\phi \succ p$ is interpreted according to the CCA application, for instance, (*i*) ϕ refers to more recently determined (up-to-date) context than p, (*ii*) ϕ represents more specific / detailed context than p, thus, one deduces p from ϕ, or (*iii*) ϕ is of better quality context w.r.t a certain indicator (quality indicator, accurate measurement) than p. In this article, we focus on the generalization / specialization relation in order to illustrate the concept of context aggravation and transmutation.

Let $\mathbf{P}(n)$ be the finite set, $\mathbf{P}(n) = \{p_1(n), \ldots, p_k(n)\}$, of k contextual parameters $p_i(n), i = 1, \ldots, k$ of level $n \geq 0$, which assume values o_i in the domain Dom_{p_i}. A contextual parameter $p_i(n)$ is *instantiated* at time t if, at time t, a value $o_i \in Dom_{p_i}$ is assigned to $p_i(n)$, that is $p_i(n) = o_i$. *Context* of n-level is the set $p(n) = \{o_1, \ldots, o_k\}$ of instantiated contextual parameters at time t. The set of contextual parameters belonging to $\mathbf{P}(0)$ (0-level) represents non-inferred context, called *ground* context; context that cannot be deduced by other parameters belonging to $\mathbf{P}(0)$ (e.g., sensor readings, $\mathbf{P}(0) = \{$*position, time, illumination*$\}$). Consider the contexts $p(n)$ and $p(m), n \neq m$. Then, *context completion* of $p(n)$ with $p(m)$ at time t is the update rule of the instantiated context $p(n)$: $p(n^*) \leftarrow p(n) \cup \{o \in \{p(n) \cup p(m) \setminus p(n) \cap p(m)\}\}$ with $n^* = max(n, m)$. As long as the $p(n^*)$ context is *completed* with additional contextual values, the CCA application might be able to infer additional context. Consider the N-ary relation f from a subset of the Cartesian product $f \subseteq \mathbf{P}(n_1) \times \cdots \times \mathbf{P}(n_N)$. If the f relation is a logical *synthesis* of instantiated contextual parameters at time t then *inferred context* $p(m) \in \mathbf{P}(m)$ of m-level, $m > 0$, is the implication $\rightarrow$ of the conjunctive parameters $p_i(n_i) \in \mathbf{P}(n_i), i = 1, \ldots, N, n_i < m$. The relation $f = (p_1(n_1), \ldots, p_N(n_N))$ can be represented as the *antecedent*-part of the implication $\rightarrow$ and the inferred context $p(m)$ as the *consequent*-part. The antecedent-part refers to the proposition $p_i(n_i) = o_i$ or simply $p_i = o_i$,

$o_i \in Dom_{p_i}$. The implication $\rightarrow$ concludes $p(m)$ of a higher level set with $m = max(n_i) + 1, i = 1, \ldots, N$, that is,

$$(p_1 = o_1) \wedge \ldots \wedge (p_N = o_N) \rightarrow p(m) \tag{1}$$

The $p(m)$ is the classification of the pattern $\{p_1 = o_1, \ldots, p_N = o_N\}$, where the elements $p_i = o_i$ can be formed by context completion. Evidently, the higher the value of m is the more information is conveyed by context. Details on a more complex context inference can be found in [2], [3].

2.2 Context Reasoning

Consider the inferred contexts $p(n) \in \mathbf{P}(n)$ and $q(m) \in \mathbf{P}(m)$ of levels $n < m$, and let $A(p(n))$ and $A(q(m))$, and $o_i^p \in Dom_{p_i}$ and $o_i^q \in Dom_{q_i}$, be the set of antecedents and the values of $p(n)$ and $q(m)$ at time t, respectively. Then, inferred context can be hierarchically structured forming transitive generalization relations $\succ$ where the semantic interpretation is defined as the following equivalence: $A(p(n)) \subseteq A(q(m)) \wedge (o_i^p = o_i^q) \leftrightarrow q(m) \succ p(n)$ with $i = 1, \ldots, |A(p(n))|$. Although $p = p(n)$ represents more *generic* inferred context than $q = q(m)$, the opposite implication does not always hold true. According to the example in Section I, $\phi \succ p$; a person attending a lecture in room *R3* implies also that, this person is located in that room. That is, a node i carrying p can be infected with ϕ leading to the transmutation of p to ϕ . If $\Phi(p)$ is the set of all pieces of context that are more generic than p, that is, $\Phi(p) = \{q | p \succ q \vee p = q\}$, then H refers to the *contextual taxonomy* of pieces of context that are associated with transitive $\succ$, that is, $H = \{p \succ q | \Phi(p) \cap \Phi(q) \neq \emptyset \vee \Phi(p) \supseteq \Phi(q)\}$. A node i can autonomoulsy reason about whether to accept *incoming* context sent by a neighboring node j or not. Consider the hierarchy $H = \{\phi \succ q, q \succ p, p \succ \psi\}$ and the fact that node i is infected with p at time t. Then, node i: (a) is probable to be infected with the stronger q at time $t+1$; context transmutation of p to q, or (b) can infer p from q. In both cases, node i accepts context q and, thus, the condition of node i is *aggravated*. If the non-occurrence of context p holds true at time t, that is, $\neg p \rightarrow \texttt{true}$, then the non-occurrence of context q is concluded, i.e., $\neg q \rightarrow \texttt{true}$[1]. This leads to the fact that, a node is *partially* recovered by any epidemic $\phi \in H$ as long as $\phi \succ q \succ p$ and remains infectious with any epidemic $\psi \in H$ as long as $q \succ p \succ \psi$. In this case, the condition of node i is *improved.* Finally, if $\Phi(\phi) = \emptyset$, node i *fully* recovers. During the (inferred) context propagation across a group of nodes, it is assumed that, all the disseminated pieces of context are *valid* (e.g., up-to-date) and the context propagation is constrained to a certain number of hops (or to a certain geographical area), i.e., only the nodes that are *members* of the *same* group can interoperate / collaborate.

[1] If, however, both p and q can be either true or false (bivalent) and p can only be true if q is true then *modus tollens* stands, i.e., $((q \rightarrow p) \wedge \neg p) \rightarrow \neg q$

2.3 Multi-epidemical Context Dissemination

The considered problem refers to the calculation of the predicted threshold of disseminating each piece of context p_k in a CCAS. We solve this problem based on an eigenvalue approach. We use a directed graph $\mathcal{G}(V, E)$ to represent a *multi-epidemical network*, where V is the set of nodes and E is the set of edges. The state of node i at time instant t is denoted by $x_i(t)$. This state assumes $K+1$ values which are represented by the $K+1$-dimensional vectors $p_k = [0, \ldots, 0, 1, 0, \ldots 0]^\top$ where all values are zero except the k^{th} component ($k = 0, 1, \ldots, K$) which takes the value 1. A state of value p_k denotes that the node is in infectious status with epidemic p_k of level k. Therefore, the most specific information that is disseminated across a network refers to inferred context p_K of level K. A node with the most susceptible status is in a state p_0 whereas a node with the most infectious status is in a state p_K. As node i can be infected only by its neighbors, the state $x_i(t)$ is statistically dependent on the status of its neighbors and $x_i(t-1)$. Since the status of a neighbor also depends on its own neighbors, the status of all nodes is statistically dependent in space and time. Let the vector $\mathbf{x}(t)$ denote the status of all nodes at time t, that is $\mathbf{x}(t) = [x_1(t), x_2(t), \ldots, x_M(t)]^\top$ where M is the number of nodes in the network. It is clear that $\mathbf{x}(t)$ is a spatiotemporal process. The infection and recovery rates β_{ji} and δ_{lk}, respectively, are very important in the epidemiological epistemic domain. The infection rate β_{ji} denotes the birth rate of an epidemic from node $j \in V_i \subset V$. Given the status of the neighbors of node i at time t and the fact that node i may be infectious at level k, at the next time instant $t+1$ node i will be infectious at a higher level l with probability

$$Q_{kl} = (1 - \sum_{m<k} \delta_{km}) \cdot \left(1 - \prod_{j \in V_i} (1 - \beta_{ji})^{x_j^T(t) \cdot p_l}\right) \cdot \prod_{j \in V_i} (1 - \beta_{ji})^{x_j^T(t) \cdot \sum_{m>l} p_m} \tag{2}$$

The second product, i.e., $\prod_{j \in V_i} (1 - \beta_{ji})^{x_j^T(t) \cdot \sum_{m>l} p_m}$, expresses the probability that all the nodes $j \in V_i$ with an infection level greater than l will not infect node i. The expression $(1 - \sum_{m<k} \delta_{km}) \cdot \left(1 - \prod_{j \in V_i} (1 - \beta_{ji})^{x_j^T(t) \cdot p_l}\right)$ is the probability that one or more nodes will infect node i at infection level l and node i will not recover. By considering a Markov chain of unit time transition periods, the transition probabilities that express the temporal dependence of states of node i are: *Full cure* case:

$$P\{x_i(t+1) = p_0 \,|\, x_i(t) = p_k\} = \delta_{k0} \tag{3}$$

Partial cure - condition improvement case:

$$P\{x_i(t+1) = p_k \,|\, x_i(t) = p_l\} = \delta_{lk}, \; 1 \leq k < l \tag{4}$$

Infection - condition aggravation at a higher level $k < l$:

$$P\{x_i(t+1) = p_l \,|\, X_{V_i}(t) = \mathbf{x}_{V_i}(t), x_i(t) = p_k\} = Q_{kl} \tag{5}$$

where, the random vector $X_{V_i}(t)$ denotes the status of all neighbors of node i, i.e., $X_{V_i}(t) = [x_j(t), j \in V_i]$ and $\mathbf{x}_{V_i}(t)$ is a realization of $X_{V_i}(t)$. The epidemical threshold for an epidemic p_k or its transmutation denotes whether an outbreak of p_k occurs (*pandemic*) or not. Therefore, the SaIS model assumes that, the node cannot become less prone after experiencing any type of infection, i.e., the infection rate remains constant. To this end we consider the Markov chain consisting of $M \times (K+1)$ states, where M is the number of network nodes and K is the number of different epidemics. The states of this Markov chain are denoted by $S_{i,k}$, which means that node i is infected by epidemic p_k. To simplify our notation we use $P^k_{i,t}$ to denote the probability that node i is infected by p_k at time t, that is $P^k_{i,t} = P\{x_i(t) = p_k\}$. Therefore, $P^k_{i,t}$ is the probability that the Markov chain is in state $S_{i,k}$ at time instant t. Writing the balance equations for states $S_{i,k}$, $1 \le k \le K$, we obtain

$$\begin{aligned} P^k_{i,t+1} = &\sum_{m<k} \sum_{\mathbf{x}_{V_i}(t)} Q_{mk} \prod_{j \in V_i} P\{x_j(t)\} \cdot P^m_{i,t} \\ &+ \sum_{\mathbf{x}_{V_i}(t)} Q_{kk} \prod_{j \in V_i} P\{x_j(t)\} \cdot P^k_{i,t} + \\ &+ \sum_{m>k} \delta_{mk} P^m_{i,t} \end{aligned} \tag{6}$$

The first line expresses the transitions into state $S_{i,k}$ from neighboring infectious nodes whose infection level is lower than k. The second line expresses the transition from state $S_{i,k}$ to itself. In this case, no cure or infection at a higher level should occur. The final sum expresses partial cure transitions from a state of node i, $S_{i,m}$, of higher infection level ($m > k$). To simplify the analysis we assume $\beta_{ji} = \beta$ and we treat each case independently. We substitute $P^0_{i,t} = 1 - \sum_{k=1}^{K} P^k_{i,t}$ and neglect all terms that involve products of probabilities. Using this approximation we obtain

$$P^k_{i,t+1} = \beta \sum_{j \in V_i} P^k_{j,t} + (1 - \sum_{l<k} \delta_{kl}) P^k_{i,t} + \sum_{m>k} \delta_{mk} P^m_{i,t} \tag{7}$$

Adopting the eigenvalue approach for solving such recursive equation we obtain that the value $\theta_k = \frac{\beta}{\sum_{l<k} \delta_{kl}}$ denotes the epidemical threshold of p_k. Specifically, p_k diminishes with an inverse rate of the partial or full cure rates $\delta_{k0}, \ldots, \delta_{k,k-1}$. For the special case of a mono-epidemical spreading, i.e., $K = 1$, we obtain the classical epidemical threshold for p_1, that is, $\theta_1 = \frac{\beta}{\delta}$ [16]. Several conclusions can be drawn. For instance, if the cure rates δ_{km} depend on the state m, i.e., $\delta_{km} = \delta_m$, or if the cure rates δ_{km} depend on the transmutation level $k - m$, i.e., $\delta_{km} = \delta_{k-m}$ then epidemic p_k dies off if p_m dies off. We state this result as a corrolary in this thesis.

3 Conclusions

In this thesis, we propose a model to reason about situational context and adapt to user reactions. Such model considers multiple kinds of uncertainties as typically occurring in estimation and inference of situations. However, knowledge related to situations cannot always lead to crisp classification due to its potential vagueness. The uncertainties pervade both the knowledge of the types of situations and the observations of unknown situations to be detected / classified. An ontological representation of situational context is also provided and approximate reasoning is adopted not only for identifying context but also for triggering actions based on the situation of the user and her past reactions / intentions. The proposed approach copes with imprecise reasoning by taking into account contextual similarity based on the *degree of situational involvement* and *system pervasiveness*. All decision-making is performed in the framework of Fuzzy Sets considering semantics (specialization, compatibility and disjoint properties) and similarity. Moreover, in the thesis, we adopted a biomimetic model for contextual information dissemination across CCA applications. Inferred context is handheld through a contextual hierarchy induced by generalization relations. Making use of such relations, context might imply further *new* context resulting in knowledge expansion across an ad-hoc network. The deduced knowledge can be diffused among collaborating nodes leading to a CCAS. We introduce the analogy between context and epidemic and extend the epidemiological model SIS to the SaIS, in the sense that: an infectious node can be re-infected by a stronger epidemic or infer new context thus aggravating its condition and can disseminate such epidemic by introducing the concept of transmutation. A stronger epidemic matches with an inferred context, denoting that each node can be re-infected with a more detailed (or up-to-date, or of better quality) context than that it has been recently infected. Hence, multiple *semantically* dependent epidemics can circulate across the network. As a result, a node is able to autonomously reason about whether to augment / infer additional knowledge or not, thus, behave more intelligently. We have presented a spatio-temporal model to study the dynamics of a multi-epidemical spreading. We study the impact of the transmutation and show that the spatially independent model incorporates detailed topology information. We model the SaIS epidemical prevalence through a Markov process. In the case of a mono-epidemical spreading (i.e., no transmutation is permitted) we obtain the exact mathematical model studied in [15]. In our generalized model, each epidemic assumes different spreading behavior and we show that such behavior may affect the spreading pattern of its transmutations. We also investigate the epidemical decay through an eigenvalue-based approach. We found the relations among the epidemical thresholds of the transmuted epidemics and observed that an epidemic p_k dies off once the largest eigenvalue of the corresponding matrix of infection level k is less than one. Such approach can be applied on arbitrary network graphs. In the case of a mono-epidemical propagation, the resulted threshold derived from our model is the classical epidemical threshold studied in [16]. Moreover, the behavior of the proposed multi-epidemical model is assessed through analysis and extensive simulations on regular lattices and social networks.

References

1. C. Anagnostopoulos, A. Tsounis, S. Hadjiefthymiades, “Context Awareness in Mobile Computing Environments”, *Wireless Personal Communications*, 42(3), pp. 445-464, 2007.
2. C. Anagnostopoulos, S. Hadjiefthymiades, “Enhancing Situation Aware Systems through Imprecise Reasoning”, *IEEE Transactions on Mobile Computing*, 7(10), pp. 1153-1168, Oct., 2008.
3. C. Anagnostopoulos, P. Passias, S. Hadjiefthymiades, “A Framework for Imprecise Context Reasoning, *IEEE Int. Conf. on Pervasive Services*, 181-184, 2007.
4. C. Anagnostopoulos, Y. Ntarladimas and S. Hadjiefthymiades, “Situational Computing: An Innovative Architecture with Imprecise Reasoning”, *The Journal of Systems and Software*, Elsevier, 80(12), pp. 1993-2014, Dec., 2007.
5. C . Anagnostopoulos, P. Mpougiouris, S. Hadjiefthymiades, “Prediction Intelligence in Context Aware Applications, *ACM 6 th International Conference on Mobile Data Management*, pp. 137-141, ACM Press, Ayia Napa, 2005.
6. A.Tsounis, C. Anagnostopoulos, S.Hadjiefthymiades and I.Karali, “Ontological Engineering in Pervasive Computing Environments”, *Web Semantics and Ontology*, (Eds. D.Taniar, W.Rahayu), IDEA Group Inc., 2006, ISBN 1-59140-905-5 (hardcover).
7. C. Anagnostopoulos, S. Hadjiefthymiades, “Imprecise Analogical and Similarity Reasoning about Contextual Information”, *Intelligent Techniques and Tools for Novel System Architectures Series*, Studies in Computational Intelligence, C. Panagiotis, P. Ilias, Kacprzyk Janusz (Eds.), vol. 109/2008, pp. 99-119, Sept., 2008.
8. C Anagnostopoulos, S. Hadjiefthymiades, Y. Ntarladimas and E. Zervas, “On the use of Epidemical Information Spreading in Mobile Computing Environments”, Special Issue on Recent Advances In Heterogeneous Cognitive Wireless Networks, *Mediterranean Journal of Computers and Networks*, 4(3), pp.91-98, 2008.
9. C. Anagnostopoulos, A. Tsounis, S. Hadjiefthymiades, “Context Awareness in Mobile Computing: A Survey, *Mobile and Ubiquitous Information Access Workshop*, Mobile HCI ’04, Glasgow, 2004.
10. C. Anagnostopoulos, Y. Ntarladimas, S. Hadjiefthymiades, “Situation Awareness: Dealing with Vague Context, *IEEE International Conference of Pervasive Services*, pp. 131-140, IEEE Computer Society , Lyon, 2006.
11. C. Anagnostopoulos, Y. Ntarladimas, S. Hadjiefthymiades, “Reasoning about Situation Similarity, *IEEE International Conference On Intelligent Systems*, pp. 109-114, IEEE Computer Society, London, 2006.
12. C. Anagnostopoulos, S. Hadjiefthymiades, E. Zervas, “An Epidemiological Model for Semantics Dissemination, *3rd ACM International Mobile Multimedia Communications*, ACM Press vol. 329/10, pp.1-6, Nafpaktos, 2007.
13. C. Anagnostopoulos, O. Sekkas, S. Hadjiefthymiades, “Context Fusion: Dealing with Sensor Reliability, *2nd IEEE International Workshop on Information Fusion and Dissemination in Wireless Sensor Networks in conjunction with 4th IEEE International Conference on Mobile Ad-hoc and Sensor Systems*, IEEE Computer Society, Piza, pp. 1-6, 2007.

14. C Anagnostopoulos, S. Hadjiefthymiades, “On the Application of Epidemical Spreading in Collaborative Context Aware Computing”, to be published in *ACM SIGMOBILE Mobile Computing and Communications Review*, 2008.
15. C. Zesheng, J. Chuanyi, “Spatial-temporal Modeling of Malware Propagation in Networks”, *IEEE Transactions on Neural Networks*, 16(5), pp. 1291-1303, Sept., 2005.
16. Y. Wang, D. Chakrabarti, C. Wang, C. Faloutsos, “Epidemic Spreading in Real Networks: An Eigenvalue Viewpoint”, *Int. Symposium of Reliable and Distributed Systems*, pp. 25-34, 2003.