Cardiology eHealth Messages Routing Policies Management Driven by Dynamic Bayesian Networks

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Abstract

The emergence of eHealth and the proliferation of mobile healthcare computing devices has led to a large increase in message transfers among remote healthcare providers and patients. Different scenarios in cardiology, such as the follow up of chronic heart diseases at home obviously require intelligent and reliable eHealth messages communication policies to proactively react in case of unexpected events (exceeded deadlines for reply,…) or context changes (chest pain increase,…). We propose a cardiology eHealth message modeling process that represents an orchestration of information systems and services for the support of context-aware, personalized, intelligent and adaptive routing policies. Several contextual data from the source (patient clinical signs), the target (healthcare professional localization), and the message content itself are taken into account for processing the message transfers. The message content is compliant with the HL7 Reference Information Model specifications. We finally demonstrate the process of inferring routing parameters such as the requested healthcare professional profile type and the routing means in function of different context values by means of Dynamic Bayesian Networks, and we highlight the routing policy adaptation process.

1. Introduction

The rapid worldwide development and use of eHealth and mHealth applications yields for an increasing number of message exchanges between several health actors and parties. In the cardiology domain, there exists a large variety of remote healthcare communication scenarios in self-care, home care (monitoring of cardiovascular patients, tele-expertise, etc.) from devices, patients or relatives, nursing auxiliaries, nurses, and also GPs, cardiologists, etc., to any healthcare professional. However, the latter may sometimes be unable to answer to the request because of commitment in another task, of vacations, etc., and the reasons for sending a message may be diverse: a worsened clinical state, routine transmission of ECG recordings, request for an appointment or for an advice, etc. A mediation system is therefore necessary for improving messages delivery in a context of ambient intelligence, according to the various needs which are greatly changing over time for each actor. Some communication management solutions were previously reported, but they remain dedicated to specific use-cases, such as emergency situations. Recently, with the proliferation of improved communication technologies, research in eCardiology has mainly focused on designing mobile cardiac health care devices, such as EPI-MEDICS [1], and intelligent and wearable devices. However, only a few studies emphasize the quality of cardiac eHealth messages transmission. In this paper, we propose a modeling of the cardiology eHealth message routing management process. This process reflects an orchestration of distributed ambient services providing intelligent, personalized and adaptive routing strategies. Most of these services manage data belonging to three types of ecosystems: source, target and message [2]. In addition, we propose a Dynamic Bayesian Network (DBN) to infer the routing parameters, viz the required delay for message reading in function of message contextual data. Moreover, to comply with the international standard in eHealth message exchange, we have based all our design on HL7 Reference Information Model (RIM) vocabulary specification [3]. We point out the RIM attributes constituting the variables of the network. We finally simulate the adaptation of the routing policy strategy in case of heart diseases descriptors variations leading to changes in interpretation.

The paper is structured as follows. In the next section, we present the cardiology eHealth message routing management process, its main services and their functionalities. We then refer to HL7 RIM attributes to build a DBN model for routing parameters inference.

2. Cardiology eHealth message routing management process

In this section, we propose a leading agent, the routing

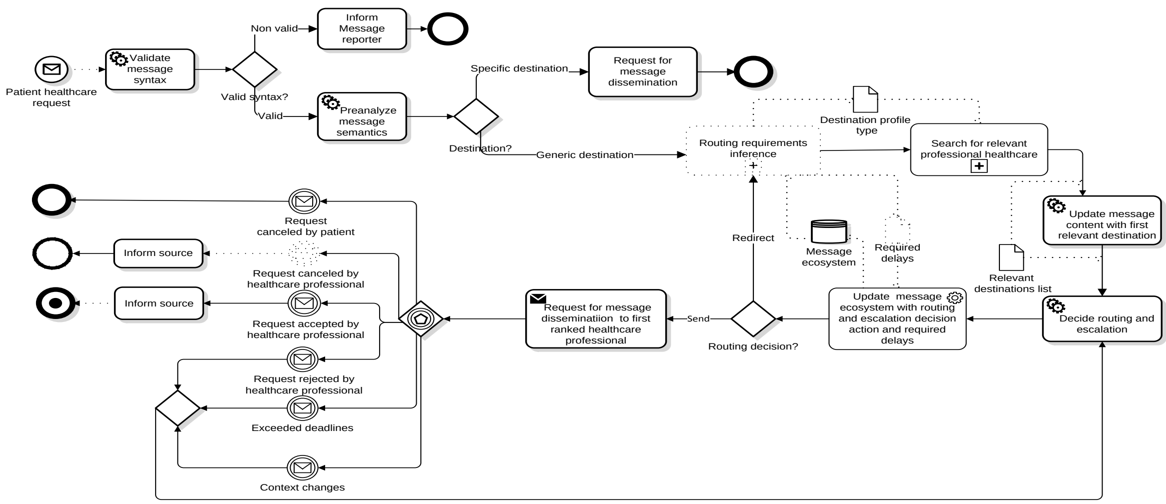

Figure 1. Cardiology eHealth message routing management process.

policy manager that will be responsible for managing the routing of cardiology eHealth messages. Using standard BPMN diagrams, we model the process executed by this agent, highlight its functionality and the corresponding services components, and show how it may behave in case of the triggering of unexpected events. This process interacts with two other processes: Message status supervision and ecosystem supervision that we have described in detail in [4]. As shown in figure 1, the cardiology eHealth message routing management starts after receiving a patient healthcare request. The latter may be issued by a message reporter, such as a mobile healthcare device, PDA, nurse call system, etc. The routing policy manager sequentially checks the validity of the syntax of the request, i.e. if it is compliant for example with international standard specifications, and pre-analyzes the request's semantics. The "message semantics pre-analysis" service includes the verification of the validity of the indication of a preferred destination by the sender. In case of undetermined destination, the present process calls for two collapsed sub-processes "Routing requirements inference" and "Search for relevant healthcare professional". The first sub-process reasons about source and message context to infer the adequate healthcare professional's profile type (medical or paramedical, general or specialist, etc.), the required material resources as well as the required delays for message reception, reading and reply. The second performs a ranking of possible, relevant message destinations according to the previously inferred profile type. A simulation of the "Routing requirements inference" sub-process model is provided in the next section. The "Search for relevant healthcare professional" sub-process creates a ranked list of possible destinations. The message is then routed to the first listed destination. In case of reception of a reject notification from the healthcare professional, of exceeding a deadline from the "message status supervision process" or of context changes from the "ecosystem supervision process", the eHealth message routing management process invokes the "decide routing and escalation" service to take the right decisions: resend or redirect, and/or possibly escalate or de-escalate. In function of these events, as well as of the history of the past actions and healthcare professional's experience and "trust level", this service decides either to resend the request to the same destination as before, to redirect it to the destination ranked second in the list, or to totally change the destination's profile type and therefore to call again the "routing requirement inference" service. For example, a decision to resend a healthcare request to the same healthcare professional may be taken at run-time if the latter is accustomed to positively respond to the majority of healthcare requests and if he has a long experience and high knowledge of the patient's health. The eHealth message routing management process ends in case of the triggering of the following two events: (1) The request is canceled by a healthcare professional (e.g. for false alarm reason) or by the patient (viz in case of pain disappearance), (2) The request is accepted by the healthcare professional. In the latter case, the two other processes, i.e. ecosystem supervision process and message status supervision process, also end.

3. DBN simulation for routing requirements inference

In this section, we highlight some of the issues raised when implementing the routing requirements inference sub-process. We capitalize on artificial intelligence technology and suggest using DBNs [5] to infer routing requirements which are necessary for delivering a healthcare request to the right healthcare professional. These parameters can be: the required delays for message reception, reading or reply, the required routing means (sms, mail, etc.), staff type (medical, paramedical), etc. To infer routing parameters, two major challenges must be taken up: time and uncertainty. Indeed, during message life cycle, the required staff type at time t for example will strongly depend on observations (e.g. message type, gravity level of clinical signs, message expeditor trust level, message routing state (initial, redirected)) at time t and at previous time t-1. Moreover, these observations may be computed from other atomic observations that may stem from uncertain sources (e.g. noisy sensors). At run-time the message may take several itineraries and follow heterogeneous routing policies according to observations evolving over time. To handle the dynamicity and uncertainty, we have adopted a DBN. A DBN is a BN (Bayesian Network) which relates variables Z_1, Z_2,.. to each other over adjacent time steps called time slices. These temporal connections incorporate conditional probabilities between variables based on the Markovian condition that the state of the system at time t depends only on its immediate past, its state at time t-1. *A DBN is defined to be a pair, (B_1, $B_\rightarrow$), where B_1 is a BN which defines the prior $P(Z_1)$, and $B_\rightarrow$ is a two-slice temporal Bayes net which defines $P(Z_t|Z_{t-1})$ as follows: $P(Z_t|Z_{t-1}) = \prod_{i=1}^{N} P(Z_t^i\,|Pa(Z_t^i\,))$, where Z_t^i is the i'th node at time and $Pa(Z_t^i\,)$ are the parents of Z_t^i in the graph* [6]. Inference in DBNs is the task of computing the probability of each state of a node in a BN when other variables are known. The inference is performed by means of a belief propagation algorithm that updates the beliefs in each variable when new observations are assigned to variables.

3.2. Building a DBN structure based on HL7 attributes

3.2.1. DBN modeling

Figure 2 shows a simplified DBN that we used to infer the routing parameter: "Required delay for message reading" in function of other variables constituting the *Message contextual data* (Gravity level of clinical history, of clinical signs, act priority, routing message state, trust level). The network is composed of identical sub-models duplicated over two time slices. The dependence between DBN variables are represented by conditional probability tables (CPT). The DBN reflects the evolving temporal process of the strategy of routing in function of the dynamicity of contextual data changes. For instance, the gravity level of clinical signs (chest pain, systolic and diastolic blood pressure, temperature, ECG interpretation, etc.) at time t may depend on the gravity level of clinical signs at time t-1. The required delay for message reading at time t may also depend on its value at time t-1. Links between two nodes indicate that there are probabilities relationships that exist between the states of these two nodes. For instance, the gravity level of the clinical history (old infarction, etc.) increases the probability of getting high gravity levels for clinical signs. Both "ActPriority", "TrustLevel", and "RoutingMessageState" can impact the "Required DelayForMessageReading".

3.2.2. DBN variables interpretation referring to RIM attributes

We distinguish two types of network variables: interpreted (trust level, gravity level of clinical history, of risk factors and of clinical signs) and non-interpreted (Act priority, routing message state). These variables aggregate several variables coming from the message expeditor ecosystem and the message content itself. In order to be compliant with international vocabulary specifications, we have built our model as much as possible on the HL7 Reference Information Model (RIM), a shared and coherent health and health care information model from which all HL7 v3 messages data content are derived. In figure 2, only the variable Actpriority exists as an HL7 RIM attribute. But several of the underlying attributes of these DBN variables are part of the RIM. They are typed in italics in the subsequent descriptions. For example, the gravity levels \ clinical signs\ clinical history are computed from *Observation interpretation normality (Abnormal, Normal), Outside threshold (Above high threshold, Below low threshold) Severity observation (High, Low, Medium)*. It is important also to know about the trust level of the Author of the Act. Indeed, the required delay for message reading for example will depend on the fact that the message expeditor is a healthcare professional (cardiologist) or not (patient family member), if he is acquainted in using advanced IT services, accustomed to send false alarms, accompanied by a healthcare professional, etc. The result of the trust level computation will thus depend on the role played by the message sender in the triggering of the act.

C_1: if (participation type = Author and Role class = patient) then

> *Trust level = f (living dependency, person disability, living situation,* accompanying*)*

C_2: if (participation type = Author and Role class = caregiver) then

> *Trust level = f (participation function,* number of false alarm, knowledge about patient illness*)*

The RIM *Participation function* attribute specifies the function played by the actor in the service. It can be an admitting physician, a discharging physician, a nurse assistant, etc. Let's note that the patient himself can be a healthcare professional. In this case, the trust level is computed from the combination of the conditions C_1, C_2.

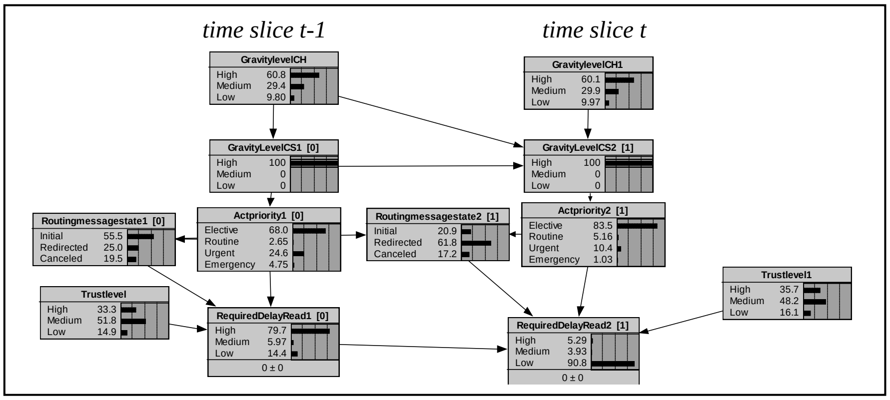

Figure 2. DBN simulation for the inference of the required delay of cardiology eHealth messages reading

Moreover, the required delay for message reading will also depend on the routing message state (redirected, initial, canceled) and to the *act priority (elective, routine, urgent, emergency)*.

3.2.3. DBN simulation scenario

One major advantage of DBNs is the capacity of adaptability. We demonstrate by the following scenario example how adding knowledge about a particular attribute can adjust the probabilities values displayed in Figure 2 and thus influence the routing policy parameter.

Scenario: Patient A has a history of cardiac disease. He visits his family living in a hostile environment (mountain), and takes his intelligent personal cardiac device with him. While arriving, he doesn't feel well. Patient A records a personal ECG and the device automatically send a minor alarm to his admitting/referral physician.

Case: Observation interpretation change - In between, patient A feels chest pain and an acute cardiac ischemia is detected by the device. The gravity level of the clinical signs has thus increased. This new knowledge constitutes an evidence or a finding entering into the DBN. As a consequence, this evidence propagates in the net and provides automatic adjustments in the nodes' probabilities of the net. The belief updating is performed by a message-passing algorithm operating on the underlying junction tree. As displayed in Figure 2, we are now almost 100% certain that the gravity level of clinical signs is now high. Thus, the probabilities of the required delays for message reading at time slice t are now totally different from the probability at time slice t-1, requiring now a "low" delay for reading the message.

4. Conclusion

Taking the right message routing decision making and improving the quality of message transmission are one of the most prominent challenges for enhancing the management of cardiac diseases. Continuous changes in contextual data may make the routing decisional process difficult. In the present research, we aimed to develop a methodology that is as generic as possible in order to be compliant with different scenarios in the eHealth domain. We used BPMN diagrams to model a distributed system for the support of context- driven, adaptive and personalized cardiology eHealth message transfers. We also emphasize the use of artificial intelligence methods (e.g. DBN) to infer the routing requirements and to make the routing decisions intelligently adaptive according to context changes.

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