STRATEGIES IN THE USE OF STATIC AND DYNAMIC BAYESIAN NETWORKS IN HOME MONITORING

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Abstract

This paper presents a methodology to use static and dynamic Bayesian Networks (BNs) in Decision Support Systems (DSS) for home monitoring. It consists of a loop around the patient, giving support both to the professional and to the patient in a more frequent follow-up.

The author presents the prototypes of a static BN for treatment guidance, and of a dynamic BN (DBN) for daily management and decompensation prediction in chronic Heart Failure (HF) patients. A validation with cardiologists for the selection and quantification of the input and output variables has been completed. The system will be validated using data from the MyHeart HF clinical study of one year of daily measurements of 200 patients.

1 Background

The saturation of western healthcare systems with increasing demands from an aging population is provoking the evolution of the medical practice towards prevention, continuum of care and home-monitoring strategies.

The introduction of new home monitoring systems that are easy to use, simple, and low cost, enables new strategies for treatment and follow-up, especially of chronic patients. Disease management systems vary in terms of technological and medical elements, however they normally consist of a patient station (for the user interaction and to collect the information from different sensors), a communication medium (fixed telephone, DSL or wireless), and a professional platform for the physician or nurse [1].

The approach of the MyHeart project is to monitor Vital Body Signs with wearable, non-invasive technology, to process the measured data and to give the user (therapy) recommendations from the system. In this Integrated Project of the European Union, a specific platform for Heart Failure Management has been developed [2], whose main objective is to improve the outcome of chronic heart failure patients with respect to mortality, morbidity and quality of life. The platform monitors daily vital body signs at the home of the patient without the need of technical or medical support, in contrast to the less frequent measurements at the doctor's clinic that are performed nowadays.

The proposed research work focuses on the application of Decision Support Systems (DSS) to complement tele-monitoring devices of the MyHeart project. The system is designed to detect changes in the patient's health status early enough to allow the timely therapy intervention from the professional, thus avoiding severe deterioration and hospitalizations due to decompensation. The end users of the system are patients with chronic heart failure (NYHA classes II-IV), and the physicians (cardiologists and general practitioners) and nurses caring for the patient.

2 Methods

The DSS added-value in home-monitoring is the ability to provide clinicians and patients with knowledge and person-specific information, intelligently adapted and filtered and presented at the appropriate time, to foster both optimal individual patient care and use of resources.

There are many artificial intelligence techniques to be used in DSS, some based in functional models of the human systems other based on data learning processes. This paper focuses on belief networks, which are based on the probabilistic theory. Inferential statistics in medicine are the foundation of evidence-based treatment, providing valid predictions based on only a sample of all possible observations, thanks to numerous techniques for stating the level of confidence of these predictions.

Bayesian Networks (BNs) are probabilistic graphical models that represent a set of variables and their probabilistic dependencies. BNs have been proven efficient in the medical field for decades, mainly providing diagnostic aids and classifiers in DSS in the hospital environment, even when not all the information is available [3].

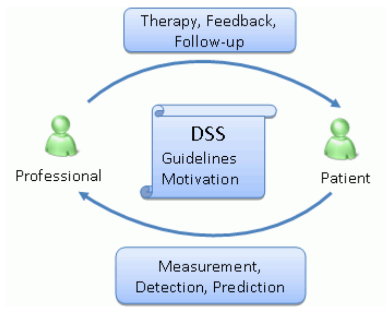

Fig. 1 DSS Closed Loop Flow

This work presents a methodology to use BNs in DSS which include a closed loop for patient management at home, giving support both to the professional and to the patient in a more frequent follow-up, as shown in figure 1.

The methodology, which is based on an existing life cycle model developed by van Zon at Philips Research [4], is described in the figure 2 and can be applied to the design of both static and dynamic BNs. As shown in the picture, there are four main phases in the life cycle model:

The decision phase corresponds to the identification of the problem and the justification of the Bayesian approach only when the problem is of probabilistic nature, can be represented by a finite number of variables, there are no circular influences and the conditional probabilities for the variables and states are stable and can be determined with realistic efforts.

The design and development phase is subdivided in the tasks of the network creation and the integration in the complete DSS. In terms of the iterative process of the network creation, it is important to delimit the boundaries of the context, defining the knowledge base, in principle with the definition of an ontology. From this knowledge model, the engineers in combination with domain experts select the variables that are relevant to the problem and the discrete ranges that provide the best results to the DSS. The structure of the network is recommended to be designed with the medical experts, while the quantification is performed in three stages: an initial assessment by the domain experts, an automatic learning from available training data, and a final validation by the experts to avoid any bias introduced by the occurrence in the data of very rare cases which overestimates certain probabilities. Depending on the size of the training data, the weight of the initial estimation is rated, in a parameter named equivalent sample size. The consideration of different sources for quantification may lead to incorrect results if it is not performed properly [5]. There are different strategies to train and validate the network depending on the size of the data set available. When there is only one large dataset available, it is recommended to use k-fold cross-validation techniques, i. e. to divide the dataset into k subsets and sequentially use k-1 sets for training and the left one for testing.

Once the network is developed it should be integrated in the complete DSS. Off-the-shelf BN software packages normally do not provide tools to elaborate the rest of the elements required in the DSS, like a user interface. An additional element usually missing in DSS is an explanation system that should provide a kind of verbal justification of the decisions. The whole system is verified with real data in a wider validation, including organizational and user acceptance aspects. At this stage policies for the updating mechanism have to be established, to decide the degree of profiling permitted.

The operations phase consists on the deployment of the DSS in a concrete environment. The system has to be customized to the local workflow and resources available. This phase includes the training of the users. Finally the lifecycle concludes with the maintenance activities, including updates and upgrades following the normal software evolution process.

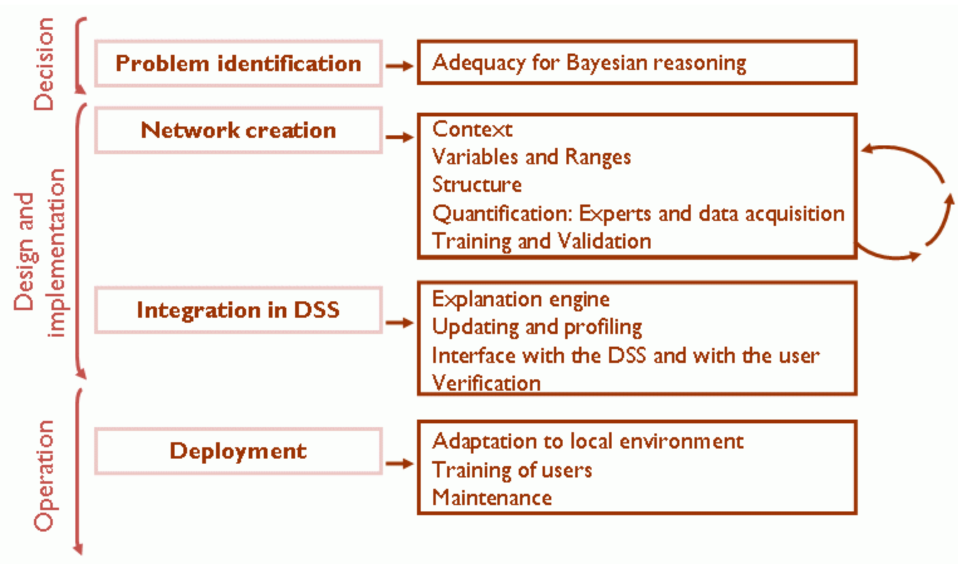

Fig. 2 BN Life cycle

3 Results

Following the scheme represented in figure 1, the DSS provides guidance for the physician in selecting the adequate treatment via a static BN and supports the daily management of HF patients in the follow-up phase, by detecting and predicting status deterioration and decompensation via a DBN.

A validation with cardiologists for the selection and quantification of the input and output variables has been completed. The system will be validated using data from the MyHeart HF clinical study of one year of follow-up with 200 patients, which will be carried out in Germany and Spain.

Static Bayesian Network

It is very common that chronic patients require a combination of drugs for the correct treatment. In the case of HF, following the evidence based medicine, most patients are on three or four medications. The DSS designed provides support to the treating physician (cardiologist or general practitioner) to select the adequate drug combination according to the medical condition of the individual and the clinical guidelines.

Figure 3 represents a simplified version of the BN designed. The nodes in orange are taken from the medical history of the patient or in the first examination; these determine the adequate medication cocktail (nodes represented in light blue). The physician and the system also take into account the reported adverse effects of the drugs and the interaction between them, which are reported in different signs and symptoms displayed in green in the figure.

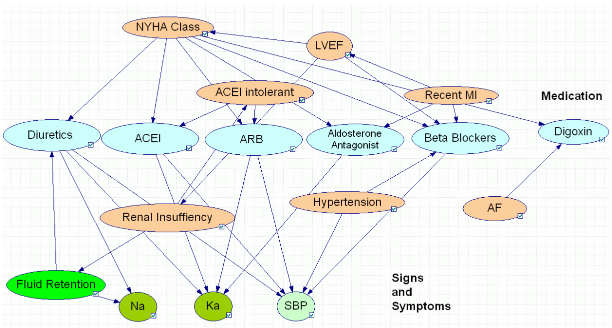

Fig. 3 Static BN for Medication Management

The network has been developed following the methodology presented in the previous section, and the structure has been designed with the support of the cardiologists of the HF team at the Clinico University Hospital in Madrid. The quantification has been performed following the guidelines of the European Society of Cardiology and the published results of clinical trials in HF management. The system provides guidance also in situations of absence of one or more of the input variables.

Dynamic Bayesian Network

DBN were introduced to provide a formalism for temporal reasoning in BN. This is of great importance in Medical applications, in which the temporal aspect is of essential significance. The DBN formalism used in this result is based on [6]. For a dynamic model, it is essential to distinguish between the variables which are static, i. e. outside the temporal plate and those which have a probability distribution for a given time period, i. e. which are affected by the temporal dimension.

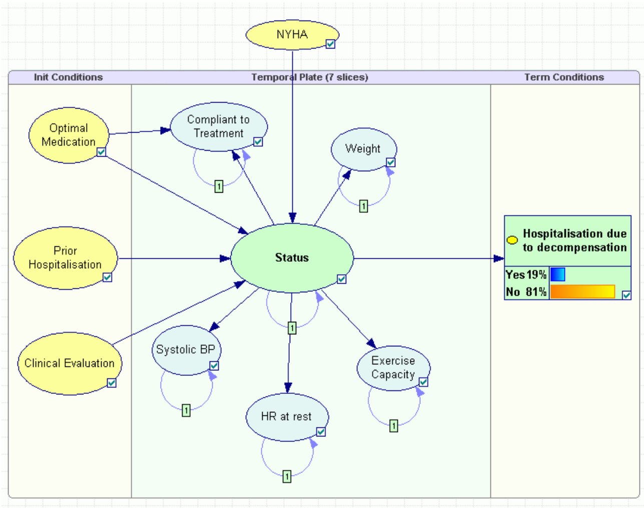

Fig. 4 Dynamic BN for HF Management

The figure 4 above shows an almost naïve dynamic network for patient management in HF. The objective is to predict the status of the patient and the risk of hospitalization due to decompensation (variables drawn in green). The entry points by the physician are represented in yellow, while the daily patient measurements and self reported items are in blue.

The dynamic or temporal plate, in the center of the drawing, contents a number T of time slices (in the figure T=7) which represent the sequence length of the unroll process. The temporal nodes affect the next "n" time slices (in the figure n=1). Temporal arcs represent the time delay of the dependency between two variables.

The nodes in yellow represent initial conditions, taken from the medical history or from the first examination. This time, a distinction should be done: there are static nodes which are constantly affecting the nodes in the dynamic plate (contemporal nodes: in the figure the node NYHA) and other static nodes which only represent initial conditions, and therefore only influence the first inference (anchor nodes: in the figure: Optimal medication, prior hospitalization and clinical evaluation).

Terminal nodes are outside the temporal plate but one or more parents are inside it; this means that a terminal node like the hospitalisation represented in green in the figure is only connected to its parent in the last time-slice of the unrolled network.

4 Discussion

This paper presents a methodology for the use of BN in medical applications, especially in home monitoring.

In the past, use of BN and DSS in clinical settings has already shown potential, but mainly to assist the professional. The key element of the presented approach is the closed loop, which does not only monitor but also provides guidance for the patients at home, putting them at the centre of the system. The introduction of temporal inference via DBN incorporates useful tools for diagnostic and prognostic reasoning, treatment selection and discovering functional interactions.

The prototypes presented show two applications for BN in home monitoring, providing support for the treating professional and also to the chronic patient in the optimal management of HF. The system does not try to substitute the clinical guidelines or the role of the professionals, but, with the help of new technologies, to foster the implementation and follow-up of evidence based therapy also outside the hospital.

BNs are interesting for knowledge representation because they allow both top-down and bottom-up inference, they facilitate decision under uncertainty, they easily capture the experts reasoning in cause-effect terms, they can learn from data, and they are easily updatable and personalisable. The availability of statistical tools and software solutions even for devices with low-computational capacity make them an interesting approach for home medical DSS.

On the other hand, BNs show some limitations as they do not provide a reasoning/explanation engine themselves, they need a lot of data/knowledge to set the adequate probability distributions, and mainly model only discrete and non-overlapping variables. On the computational side, solving a particular situation always requires to solve the complete BN, so even almost trivial reasoning need certain computational power and time.

BN have a qualitative and a quantitative component. The qualitative element is the structure of the network, which can be discussed and easily extracted from experts knowledge. The difficult part is the quantitative one, i.e. the conditional probability distributions, which determine the exact relationship between states and variables.

5 Conclusions

Using graphical representation, BN are a good DSS tool for discussion with medical experts and the BN can combine the expert knowledge with patient data for handling the uncertainty involved in establishing diagnoses, selecting optimal treatment and predicting treatment outcomes.

The limited availability of daily patient monitoring data for the training and validation of the BN is the main difficulty for these models. This highlights the necessity of clinical trials to collect unbiased information about the sensing technologies at home and to validate DSS models for home monitoring.

These systems may also be integrated with other Information Systems in the hospital, such as laboratory exams or patient history registries, to facilitate the personalization and updatability. In these cases, strategies for data privacy and anonymisation are essential.

Acknowledgement

This work was supported by the European Marie Curie Transfer of Knowledge Program. Project AIMed, Advanced Intelligent Medication - personalized drug dosage concepts to improve quality of life. [TOK-14459].

The research was based on the results from the MyHeart Project [IST-2002-507816].

The authors are grateful to Kees van Zon from Philips Research Laboratories in Briarcliff (USA) for his valuable inputs to the research work.

References

[1] Roccaforte R., Demers C., Baldassarre F., et al. Effectiveness of comprehensive disease management programmes in improving clinical outcomes in heart failure patients. A meta-analysis. European Journal of Heart Failure, vol 7, no. 7, pp. 1133-1144

[2] MyHeart IST-2002-507816 project (2004). Information available on http://www.cordis.lu/ist

[3] Nikovski, D. Constructing Bayesian Networks for Medical Diagnosis from Incomplete and Partially Correct Statistics, IEEE Transactions on Knowledge and Data Engineering, vol. 12, no. 4, pp. 509-516, Jul/Aug, 2000

[4] van Zon, K. The Bayesian Network Lifecycle. Technical Note PR-TN-2006/00155. Export review: EAR99 NLR. Philips Research North America, NY, USA 2006

[5] Druzdzel, MJ. and Diez, FJ. Combining knowledge from different sources in probabilistic models. Journal of Machine Learning Research, vol. 4, pp. 295-316, Jul 2003.

[6] Hulst J. Modeling physiological processes with dynamic Bayesian networks. Master thesis. Delft University of Technology. 2006