e-MomCare: A Personalised Home-Monitoring System for Pregnancy Disorders

Marina Velikova[1], Peter J.F. Lucas[1], and Marc Spaanderman[2]

[1] Institute for Computing and Information Sciences,
Radboud University Nijmegen, The Netherlands
{marinav,peterl}@cs.ru.nl
[2] Department of Obstetrics and Gynaecology,
Radboud University Nijmegen Medical Centre, The Netherlands
M.Spaanderman@obgyn.umcn.nl

Abstract. We present a novel intelligent on-line system for home-monitoring of pregnant women that is developed to offer pregnant women personalised care. Present home-monitoring devices are restricted as they only collect physiological parameters and send them to a personal computer or cell phone for data storage and visualisation. In our work, however, we focus on the development of a probabilistic model that, based on the data available from different sources, is able to predict the evolution of a pregnancy disorder, here preeclampsia. The paper outlines the basic components of the system, describes in detail the decision-support model based on Bayesian networks, and report preliminary system's application results using real patient data.

1 Introduction

In the modern world, people are feeling increasingly responsible for their health, and many people, in particular when young, wish to be involved in making decisions about their health or disease. Measures taken to realise this have been referred to as *patient empowerment*. A particularly important measure is adapting general decision-making models to the individual's characteristics, usually referred to as *personalisation*. Personalisation of care can be applied in various forms ranging from a simple adjustment of a system's settings to the user's capabilities, to a more complex degree of system's adaptation capturing the entire patient's environment. Various electronic personalised monitoring systems have been proposed in the literature. In [7] the authors propose a medical embedded device for individualised care allowing adaptive sensor management and autonomous diagnostic inference based on probabilistic methods. To supervise a physical fitness activity, in [1] a wearable mobile personal trainer system is proposed, based on alternating jogging and fitness exercises in an open-air environment. An intelligent personal monitor is proposed in [6], where a committee of artificial neural networks is used to raise alarm for unwanted cardiac events.

Pregnant women are certainly another group of people who normally wish to be involved, and at least informed, about relevant decisions made by health-care

M. Szomszor and P. Kostkova (Eds.): E-Health 2010, LNICST 69, pp. 267–274, 2011.

professionals during the course of their pregnancy. When the pregnancy is the cause of illness, such as is the case with *(pre)eclampsia*—a syndrome characterised by high blood pressure, or hypertension, and associated deterioration of renal and cardiovascular function—clinical intervention is needed to protect the lives and health of both mother and child. Thus, when there is a suspicion that the pregnant female will develop (pre)eclampsia, she becomes a *patient* who is checked on a regular basis by the gynaecologist. Yet, we believe that e-Health methods and techniques can contribute to improving the quality of this care to this group of patients by offering person-centric devices that can provide feedback and decision support regarding the progression, or lack thereof, of the disease. Such decision support could in principle offer greater involvement and control of the patient on her disease.

In this paper we present a prototype of a decision-support system, the *e-MomCare system*, that can be used on a smart phone, with the, in principle, possibility to collect and exchange information between patient, measurement devices (e.g. blood pressure device), and the hospital information system. Novel in this research in comparison to existing electronic solutions, mostly devices that collect physiological parameters and send them to a personal computer or cell phone for visualisation or for dispatching the patient data to a central data server, is that our work focuses on the development of a model that, based on the data available from different sources, will be able to *predict* evolution of the disorder, in our case (pre)eclampsia. Thus the decision support offered will be *intelligent*, which will allow replacing some of the feedback that a gynaecologist can offer by feedback from the decision-support system.

2 Preeclampsia

Preeclampsia is a significant clinical problem. Approximately 15% of first-time pregnant women develop high blood pressure and approximately half of them develop associated problems, such as kidney damage and subsequent proteinuria (leakage of serum protein into the urine), leading to the syndrome of preeclampsia. The latter is often diagnosed after 20 weeks of pregnancy or immediately after the delivery and it is the most important cause of death among pregnant women in the Netherlands and a leading cause of fetal complications. As a pregnancy-related condition the only way to cure preeclampsia is to deliver the baby. However, early anti-hypertensive treatment in the subclinical, mostly moderately hypertensive phase, reduces the risk of getting preeclampsia.

The timely diagnosis of preeclampsia is a non-trivial task. If a woman has an underlying renal or cardiovascular disease, the diagnosis of preeclampsia may not become clear until the disease becomes severe. This requires frequent outpatient checks, increasing the working pressure for the second- and third-line healthcare centres. During the regular outpatient visits the health condition of a pregnant woman is monitored by taking a number of measurements such as maternal blood pressure, heart rate and urine analysis.

In our current research we focus on predicting the chance of developing preeclampsia given the risk factors and the measurements of the patient obtained

from the early check-ups at 12 and 16 weeks. At this stage, early deviations in blood pressure may indicate circulatory maladaptation which often precedes preeclampsia at a later stage. Timely detection allows closer surveillance of those patients at risk; it also gives the opportunity to start with preventive medication. Common risk factors [5,3] include a family or personal history of preeclampsia, chronic hypertension, kidney disease or diabetes. For parous women, i.e., women who have given birth, without a history of preeclampsia the risk of developing preeclampsia is low.

3 The e-MomCare System

Patient data for the aforementioned risk group of pregnant women are currently collected in the outpatient clinic, requiring the patient to come to the hospital. However, large amounts of such data can also be collected at home and automatically sent to the health-care team, which provides a number of advantages: (i) it yields values that are closer to the real physiological values, as the effect of the medical doctor on the blood pressure, the so-called 'white-coat effect', is eliminated, (ii) there will be no need for the patient to frequently visit the hospital and she can be actively involved in her own medical care; (iii) the working pressure on midwifery care can be reduced, and, health-care costs can be possibly safed.

We investigate electronic home monitoring of patients at risk via the Internet, so that patient data is automatically available to the care team. This form of home monitoring requires an intelligent system, because it is desirable that both doctor and patient get an insight into the patient's health status and need for care without additional efforts, such as frequent telephone contacts. Of course, appropriate security must also be ensured.

Given the role of cause-effect relationships in describing physiology and the inherent uncertainty in the medical domain, we decided to use Bayesian networks to construct a model for predicting preeclampsia. The model is required to offer advice on the progression of the disease based on the physiological measurements of the patient and to inform the patient and the care team whether or not action should be taken. The actual development of the Bayesian model is also part of the current research, because such a model does not exist yet.

4 A Predictive Model of Preeclampsia

4.1 Bayesian Networks and Causal Independence

A *Bayesian network* is defined as a pair BN $= (G, P)$, where G is an acyclic directed graph (ADG) $G = (V, E)$ and P is a joint probability distribution of the random variables X. There exists a 1–1 correspondence between the nodes in V and the random variables in X; the (directed) edges, or arcs, $E \subseteq (V \times V)$ correspond to direct causal relationships between the variables. A Bayesian network BN offers a compact representation of the joint probability distribution

P in terms of local *conditional probability tables* (*CPTs*), by taking into account the conditional independences represented by the ADG.

To specify interactions among random variables in a compact fashion *causal independence* is often used, as it allows decomposing a probability distribution in terms of a Boolean interactions among local parameters [4]. Use of causal-independence models makes it easier to deal with problems involving a large number of causes, a situation that is common in domains such as medicine. The general structure of a causal-independence model expresses the idea that causes $C_1, \ldots, C_n$ influence a given common effect E through intermediate variables $I_1, \ldots, I_n$ and *interaction function* f representing the way the intermediate effects I_j, and indirectly also the causes C_j, interact. This function f is defined in such way that when a relationship between the I_j's and $E = 1$ is satisfied, then it holds that $f(I_1, \ldots, I_n) = 1(true)$; otherwise, it holds that $f(I_1, \ldots, I_n) = 0$. Each variable I_j is only dependent on its associated cause C_j and the effect variable E, and the effect variable E is conditionally independent of each cause C_j given the associated intermediate variable I_j.

4.2 Bayesian Network Model for Preeclampsia

The initial Bayesian-network model we developed was based on the risk factors and laboratory measurements taken during the check-ups at 12 and 16 weeks of pregnancy; see Fig. 1. The set of risk factors as defined here have an impact on the functioning of the cardiovascular system and hence, they determine the risk for cardiovascular dysfunction, which for brevity we referred as to *vascular risk* (VascRisk). In the Bayesian network model, these cause-effect relationships would be represented by the 'RiskFactor$_i$ $\rightarrow$ VascRisk', $i = 1, \ldots, 11$, structures. To define in a compact fashion the CPT of VascRisk given all possible combinations of risk factors, we employed causal independence, as described in Section 4.1, by adding the intermediate (hidden) variables I_j, $j = 1, \ldots, 9$. Note that the family history of diabetes / hypertension (FH-Diab, FH-HT) and diabetes / chronic hypertension (Diabetes, Chronic-HT) have a combined effect on VascRisk, represented by one hidden variable. According to the domain knowledge the risk factors interact by adding up to the vascular risk, so we choose naturally the logical OR as a function to represent these interactions.

Given the definition of preeclampsia in Section 2, the renal and vascular functioning were considered as the two major health parameters determining the syndrome. In our modelling scheme these functions are represented as two binary variables with values of *ok* and *nok* (not ok), indicating the respective function status. Note that these variables are more abstract and they do not have a direct measurement. However, as discussed earlier, several laboratory tests are performed at every check-up in order to determine the current health status, including the renal and vascular function, of the patient. The most common and easily made measurements at 12 and 16 weeks are the systolic and diastolic blood pressure (SBP, DBP) reflecting the status of the vascular function, and haemoglobin (Hb), creatinine (Creat) and the protein (albumine) to creatinine ratio (PA/C), reflecting renal function. In addition, the values for

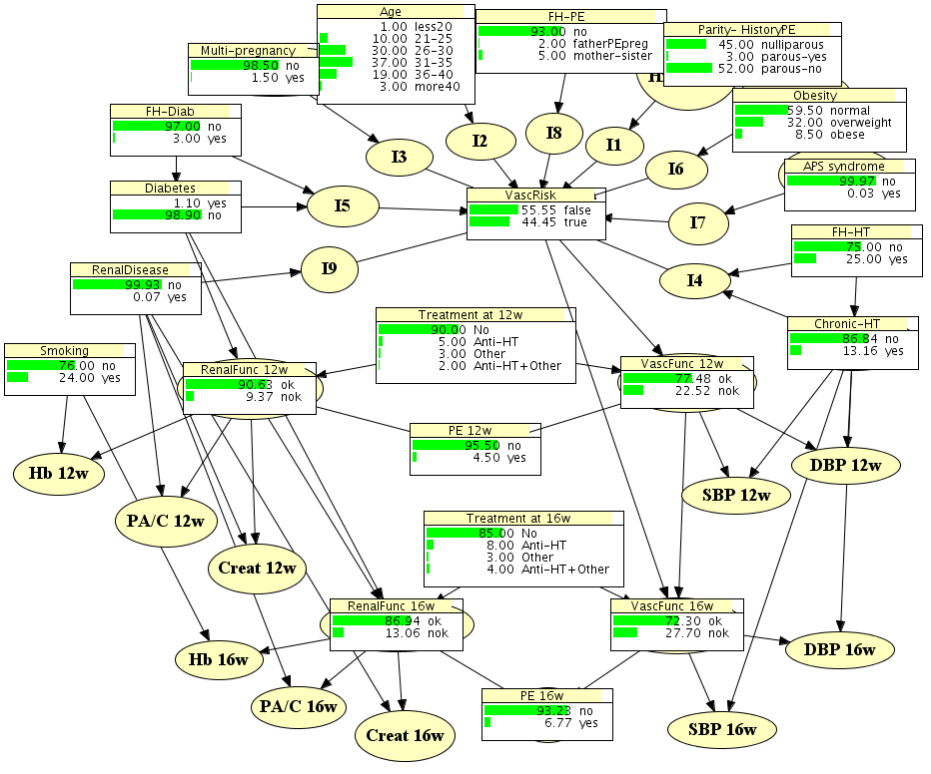


Fig. 1. Prior marginal probability distributions of the dynamic Bayesian network model for preeclampsia with laboratory tests at 12 and 16 weeks

these measurements are explained by the presence of certain risk factors. Except the laboratory measurements, however, any drug taken by the patient at the time of the check-up, has an impact on the status of the renal and vascular function, which is captured by the 'TREATMENT → FUNCTION' structure.

To capture the temporal development of both renal and vascular functions, we created a dynamic model by adding links between the respective function status at the 12 and 16 week check-ups. As a result, the combined status of the renal and vascular function determine the development of preeclampsia at each check-up. This modelling scheme allows us to estimate the probability of preeclampsia at early stages and can serve as a warning system. We estimated the probability distribution of the network's variables based on literature studies, expert opinion, and the sources discussed in Section 2. The prior, marginal probability distributions of the network are shown in Fig. 1.

Using the model, the patient and doctor can obtain insight into the development of preeclampsia by comparing to a reference group adjusted for gestational age and to the expected course based on the baseline early in patient's

Table 1. Predicted probabilities for PE by the dynamic Bayesian network model for four patients (two with and two without PE) based on their characteristics and control measurements at 12 and 16 weeks; N/A = "Not Available"

Variable	Patient 1		Patient 2		Patient 3		Patient 4	
PREECLAMPTIC PATIENT?	YES		YES		NO		NO	
PARITY-HISTORYPE	parous-yes		parous-yes		nulliparous		parous-yes	
CHRONIC HT	no		yes		yes		no	
AGE	26-30		36-40		31-35		26-30	
OBESITY	normal		obese		normal		normal	
SMOKING	yes		no		no		no	
	12 wk	16 wk	12 wk	16 wk	12 wk	16 wk	12 wk	16 wk
SPB	126	119	176	141	110	120	126	109
DPB	66	74	96	82	65	71	81	63
HB	7.6	N/A	8	N/A	7.6	N/A	7.6	N/A
CREAT	54-57	N/A	62-65	N/A	< 45	N/A	58-61	N/A
PA/C	0-0.03	N/A	N/A	N/A	0-0.03	0-0.03	N/A	N/A
TREATMENT	Other	Other	Anti-HT +Other	Anti-HT +Other	Other	Other	Other	Anti-HT +Other
P(PE=yes)	9.2%	18.6%	88.3%	43.3%	0.2%	2.5%	41.7%	4.7%

pregnancy. We studied the performance of the dynamic Bayesian network model with actual data from patients with and without preeclampsia. Table 1 presents the patient's characteristics and the probabilities computed from the model for four patients: two with and two without preeclampsia (PE). For Patient 1, we observe that the initial risk for PE at 12 weeks increases twice the prior of 4.5% and it further doubles at 16 weeks. This increasing trend can be considered as a warning sign for the development of PE, which eventually turned out to be the case. For Patient 2, who also develops PE, the initial risk for PE is very high and although it drops (as expected due to the intake of medicine) it still remains high at 16 weeks. For Patient 3, who is a non-preeclamptic patient, the characteristics and check-up measurements indicate almost a zero risk for PE at 12 weeks and it increases at 16 weeks but it still remains under the prior risk. For Patient 4, we observed a relatively high initial risk for PE but after adjustment of the drugs the chance for PE at 16 weeks drops to the prior risk; this patient remained eventually non-preeclamptic. Although these results concern few patients and are, thus, still preliminary, they indicate that the model is already able to capture a developing trend for the development of PE at an early stage.

5 Implementation of the e-MomCare System

We have opted for a smart phone as the development platform, as it offers certain advantages in comparison to an Internet-attached PC: (i) the patient is caring the smart phone and has access to its functionality anywhere and anytime and (ii) reminder functions of the need of taking measurements at any time can be easily implemented as a smart phone is usually on. Implementation of part of the system using Google's open source *android* operating system is currently seen by us as an interesting option. The system architecture is visualised in Fig. 2.

The Bayesian network model was built with the publicly available java-based

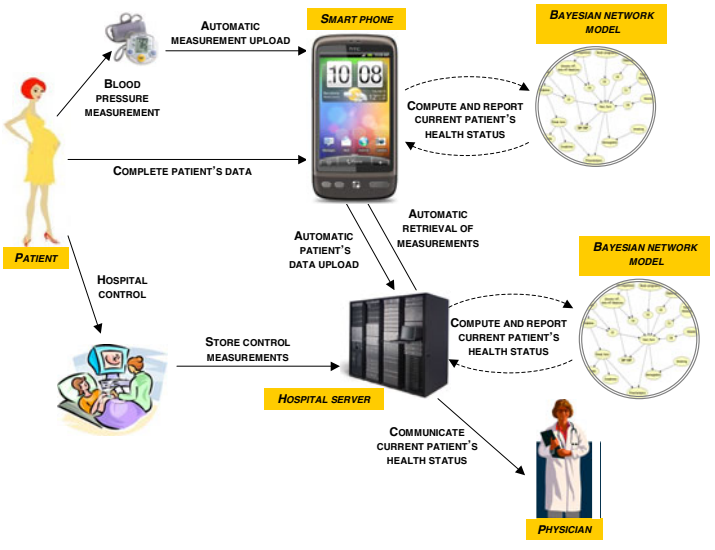
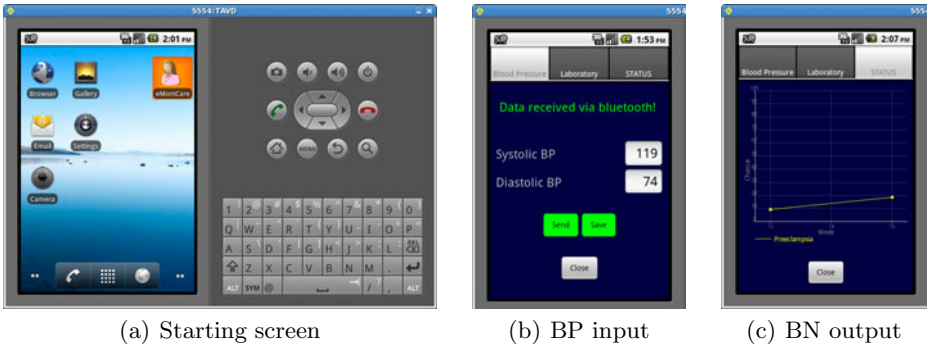


Fig. 2. Schematic representation of the module interactions in the e-MomCare system

Bayesian network package EBayes [2], which provides platform-independent engine for performing inference given evidence in the network. The java version of the network was subsequently embedded in the android application. Although we are still investigating the appropriate design concerning the user interface and communication capabilities of the smart phone, in Fig. 3 we present some of the main components of the system to give a general impression of its usability.

One of the main screens concerns the input of the blood pressure measurements, which are to be obtained via a bluetooth connection from a measuring device (Fig. 3b). In case of transmission problems, the patient is still provided



(a) Starting screen (b) BP input (c) BN output

Fig. 3. Snapshots of the system interface on android emulator for the input / output data of Patient 1 from Table 1

with the option to manually insert the blood pressure (BP) measurements. Next, she can submit the data (via the button 'Send') to the hospital server and save the measurements (via the button 'Save') in the mobile phone to allow local access. Via the tab 'STATUS' the pregnant woman can obtain her current health condition trend resulted from the inference in the Bayesian network model using the latest measurements and the previous controls (Fig. 3c).

6 Conclusions and Future Work

In this paper, we presented a prototype of an electronic system for home monitoring of pregnant women. At the current stage of development, we have a temporal Bayesian network model that is able to predict the development of preecampsia during the first trimester. Using data of pregnant women from the hospital we have been able to obtain a rough indication whether the model makes sense. Currently we work on extending the model for the whole pregnancy period allowing for more check-up measurements. For a more extensive performance validation study of the model, we are also collecting patient data in collaboration with the clinicians within the Radboud University Nijmegen Medical Centre. Finally, we are also designing a communication infrastructure to extract data from the hospital information system and to communicate patient data entered into the home environment to the hospital information system.

Acknowledgments. The work has been funded by the STITPRO Foundation.

References

1. Buttussi, F., Chittaro, L.: MOPET: A context-aware and user-adaptive wearable system for fitness training. Artificial Intelligence in Medicine 42(2), 153–163 (2008)
2. Cozman, F.G.: EBayes: embedded Bayesian networks (1999), `http://www.cs.cmu.edu/~javabayes/EBayes/index.html`
3. Duckitt, K., Harrington, D.: Risk factors for pre-eclampsia at antenatal booking: systematic review of controlled studies. BMJ 330(7491), 565–571 (2005)
4. Heckerman, D., Breese, J.S.: Causal independence for probability assessment and inference using Bayesian networks. IEEE Trans. on SMC–A 26(6), 826–831 (1996)
5. Ness, R.B., Roberts, J.M.: Epidemiology of pregnancy-related hypertension. In: Lindheimer, et al. (eds.) Chesley's Hypertensive Disorders in Pregnancy. Academic Press, London (2009)
6. Rubel, P., Fayn, J., Simon-Chautemps, L., Atoui, H., Ohlsson, M., Telisson, D., et al.: New paradigms in telemedicine: Ambient intelligence, wearable, pervasive and personalized. Wearable eHealth Systems for Personalised Health Management: State of the Art and Future Challenges 108, 123–132 (2004)
7. Wu, W.H., Bui, A.A.T., Batalin, M.A., Au, L.K., Binney, J.D., Kaiser, W.J.: MEDIC: Medical embedded device for individualized care. Artificial Intelligence in Medicine 42(2), 137–152 (2008)