

Tele-Monitoring for Medical Diagnosis Availability

D**Calin Ciufudean***Stefan cel Mare University, Romania***Otilia Ciufudean***ARENI Medical Center, Romania*

INTRODUCTION

As modern world evolves, so does the technique, economy, the life style, and unfortunately, the diseases; therefore, nowadays mainly due to stress, pollution and rush life style we confront with a new medical problem: the diagnosis of multiple diseases and the diagnosis of mutant diseases. In an optimistic case, doctors are confronted with patients who suffer from one disease and the diagnosis tries to find the cause and the most adequate treatment (Cacioppo & Tassinari, 1990), (Lyons, Budynek, & Akamatsu, 1999). This approach give birth to classic diagnosis, e.g. to ordered tables or lists well known in medicine as well as in medical informatics that make a correspondence between symptoms and disease (Ekman, Levenson, & Friesen, 1983), (Ekman, Friesen, & Ellsworth, 1972), (Posner, Russell, & Peterson, 2005). In our view this is only the starting point for developing a new way for applying computational modeling techniques in medical diagnosis procedure. This is explained by the fact that while in the above mentioned rule-based systems deterministic models are considered (e.g. there are facts determined by certain factors), our approach deals with dependent probabilities of medical symptoms, signs and tests, and therefore we model the diagnosis procedure with Markov chains. Basically, the doctors' expertise based on clinical symptoms, physical examination and laboratory results are the foundation for a correct diagnosis and treatment procedure for the patients. In order to optimize this complex process and to help performing correct computational modeling diagnosis our paper focuses on built-in diagnosis procedure (Picard, Vyzas, & Healy, 2001), (Groshan, 2012).

This chapter is organized as follows: section 2 presents our tele-monitoring framework diagnosis approach, section 3 deals with Markov models for performing built-in diagnosis, section 4 illustrates our approach by an example and section 5 concludes the present work and gives a few directions for future research in the area.

THE BUILT-IN MEDICAL DIAGNOSIS PROCEDURE

The diagnosis computational algorithm we propose consists of splitting the patient's symptoms and signs into basic or elementary ones and grouping them with corresponding medical tests (e.g. determining the components of the diagnosis), then performing the diagnosis for each component, verifying the components functionality according to the patient's symptoms and signs and determining the final diagnosis by analyzing the components interdependence functionality.

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In order to have a better look of the medical performance, we monitor the patient's evolution and the interaction between medical personnel and the patient in order to adjust the diagnosis and/or the medication whenever is necessary for improving the patient's status.

All this procedure is modeled with Markov chains which require no large dimensions mainly due to the partitioning algorithm and also to the structure we propose for these Markov chains. The partitioning algorithm of patient's symptoms has the advantage that it covers the patient's possible illness and complications of a certain treatment by reducing non-necessary patient traffic between different hospital sections and departments for performing medical investigations and therefore, saving precious time and money for both patient and medical health care system. Like in a fault tree diagnosis system, we may say that our diagnosis model concerns partitioning the system graph (e.g. the system Markov chain model) and that allows us to avoid construction of large Markov chains for each partition and to combine the diagnosis for each partition in order to obtain the general, e.g. final, diagnosis by using a causal diagnose cognitive map (CDCM). CDCM is a Markov chain that deals both with the technical devices involved in medical diagnosis and treatment as well as with the activity of the involved medical personnel. The medical diagnosis partitioning procedure is given schematically in Figure 1. Figure 1 shows that a CDCM is built for each component as we can determine the influence of the most significant component into the final diagnosis. Basically a component diagnosis represents an interface between physician and patient and consists of several provided operations and some expected or required reactions. Our approach consists of determining the optimum diagnosis, considering accuracy and time consuming, by using a built-in test of the diagnosis components model implemented with a Markov chain.

MARKOV CHAIN MODEL OF BUILT-IN DIAGNOSIS

We assume that diagnosis of patients implies some risks and also some possible human errors or lack of an adequate logistics such as materials, equipment, medical devices, etc. (Pearl, 1988), (Perner, 2006), (Perner, 2008). All these drawbacks are modeled with the CDCM by introducing the parameters "imperfect coverage, c_m " and "rate of successfully recovery of the patient after an incorrect diagnosis, r_m ". To explain the impact of imperfect coverage we consider the system in Figure 3 which includes the main elements of the medical diagnosis: laboratory analysis and patient's symptoms.

If the coverage of the system in Figure 3 is perfect (i.e. $c_m = 1$) then the diagnosis is correct as long as both main elements (laboratory tests and analyses, and patient's symptoms) are available. If the coverage is imperfect, then the diagnosis is false with probability $1 - c_m$, if one of the main elements is not available (Shepherd, 1966), (American Iatrogenic Association, 2008). The Markov chain model will ensure the availability of the diagnosis by using a lower bound of component i , where $i = 1, 2, \dots, k$, and $k \leq n$; n being the total number of components (e.g. partial diagnoses). The Markov model (e.g. CDCM) for component i is shown in Figure 4.

In Figure 4 we used the following notations: λ_m = the rate of having incorrect diagnosis; μ_m = the rate of recovering the patient after an incorrect diagnosis; c_m = the imperfect coverage; r_m = the rate of successfully recovery of the patient after an incorrect diagnosis (Martens, McMahon, 2008), (Samuel, Cavallo, 2011), (Perner, 2002), (Perner, Jänichen, 2009). According to Figure 4 a patient can be in one of the following states due to component i : The state N_i = the normal state in which all the N_i factors (e.g. laboratory analysis and patient's symptoms) in the system participate in the diagnosis process; The state k_i = the state in which k_i ($k_i \leq N_i$) elements participate in the diagnosis process; The state FK_{i+u} = the patient's state due to an incorrect diagnosis or treatment, where $u = 0, 1, \dots, N_i - K_i$; The state FK_i

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