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Multi-step prediction of pulmonary infection with the use of evolutionary fuzzy cognitive maps ☆

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ABSTRACT

The task of prediction in the medical domain is a very complex one, considering the level of vagueness and uncertainty management. The main objective of the presented research is the multi-step prediction of state of pulmonary infection with the use of a predictive model learnt on the basis of changing with time data. The contribution of this paper is twofold. In the application domain, in order to predict the state of pneumonia, the approach of fuzzy cognitive maps (FCMs) is proposed as an easy of use, interpretable, and flexible predictive model. In the theoretical part, addressing the requirements of the medical problem, a multi-step enhancement of the evolutionary algorithm applied to learn the FCM was introduced. The advantage of using our method was justified theoretically and then verified experimentally. The results of our investigation seem to be encouraging, presenting the advantage of using the proposed multi-step prediction approach.

1. Introduction

Fuzzy cognitive map (FCM) is a soft computing tool, which combines elements of fuzzy logic and neural networks [1]. In fact, it is a methodology for representing real world problems in terms of concepts and causal relationships among them. The concepts used by a decision-maker are represented as nodes, and the causal relationships between these concepts are represented as directed edges. Each edge is assigned by a weight, the real value that characterizes the effect of the causal relationship between nodes. This representation gives a graph of nodes and arrows in which the concepts are considered as variables of the system [2]. Given an initial state of a system, represented by a set of activation values of its constituent concepts, an FCM can simulate the development of a real world process (such as pulmonary infection) over time. Just because FCMs is well suited to represent approximate knowledge and have several other desirable properties [3,4], such as abstraction, flexibility, adaptability and fuzzy reasoning, the application examples can be found in many diverse scientific areas; i.e. in decision-making methods, geographical information systems, agriculture, management, and prediction of time series [5–7]. There are also some applications in supporting medical decision-making [8–10].

In many research works on FCMs, the causalities are still quantified based on expert knowledge. But for various practical problems, it is a hard task for human experts to accurately pre-specify the causalities among concepts which constitute a specific causal system. To deal with this problem, the learning algorithms applicable to FCMs have been proposed [11–13]. Mateou et al. [14] proposed the evolutionary FCMs for multi-objective optimization problems and applied it to political management. At the same time, Stach et al. [15] proposed the real coded genetic algorithm (RCGA) for FCM learning showing an important direction to the automatic construction of FCMs from raw data.

It was shown [16] that the RCGA algorithm outperforms the other learning algorithms considering a single-step prediction task. To the best of our knowledge, there is no any existing learning algorithm for FCMs that considers a multi-step prediction. It is shown that for longer prediction horizons, the prediction errors always propagate between concepts of FCM and they are independent on which type of FCM is used. This propagation of errors is neglected during the learning of FCM by all known adaptive and evolutionary algorithms. This means that the existing FCMs are not optimized for longer prediction horizons. Thus, in this paper, we propose a multi-step approach to learning of FCMs. Our approach could be used by diverse learning algorithms, however we selected the best already known single-step learning algorithm (called RCGA) to extend the learning approach to a multi-step one.

☆ This document is a collaborative effort.

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In previous works on RCGA the learning and testing data were generated from existing FCMs. These types of data were produced as synthetic multivariate time series and never involved some characteristics that are hard to be modeled by FCMs. Moreover, such types of data do not involve missing values or measurement errors that are depicted in real world. We would like to notice that in comparison to artificial neural networks (ANN), the FCMs are not universal approximators [17]. In order to model the cause-and-effect relation, the FCMs are stronger biased and many real sequences of data are hard to be efficiently approximated with the use of FCMs. Thus, the advantage of using FCM instead of ANN is such that FCM is transparent (not a black box model) to the user and the cause-and-effect relation represented by the structure of FCM graph could be interpreted by the domain experts.

Our study is focused to present a different method based on evolutionary FCMs to predict real sequences of data through a multi-step approach instead of using only one step. The contribution of our paper includes:

- a dedicated to multi-step prediction evolutionary learning algorithm for FCMs,
- the application of the proposed multi-step approach for the prediction of pneumonia that solves the addressed medical problem,
- the use of 15 concepts that best learn one of the largest existing FCMs that is based on real data.

The structure of the paper is as follows: Section 2 describes the background of the medical problem; Section 3 gives the main aspects of FCMs. In Section 4, the problem formalization is established, followed by the analysis of propagation of errors during the reasoning with FCM in Section 5. Multi-step prediction using FCM approach is described in Section 6, whereas the computational experiments are depicted in Section 7. The conclusions are gathered in Section 8.

2. Medical problem background

Pulmonary infection is an infection of the lower respiratory tract that represents a major cause of morbidity and mortality worldwide. Patients with severe pneumonia should receive intensive care. Pneumonia is suspected on the basis of patient's symptoms and findings from physical examination [18]. After pneumonia suspection further investigations especially based on laboratory studies are needed to confirm the diagnosis [19]. Laboratory studies should be performed that include blood cell counts, serum glucose, transaminases, urea, creatinine and electrolyte measurements. These data provide a logical basis for evaluating the severity of pneumonia and the need for intensive care.

The prediction of patient's state is required to make a proper medical intervention, e.g. the prescription of a drug. The task targeted in this paper is the prediction of the state of pneumonia which is further assessed by the physician to make the prescription and final decision on medical intervention.

The existing methods apply rules to classify a patient to a group of risk, but do not support a doctor during the therapy. Usually, the classification rules are given by doctors. In fact, the pneumonia severity index [20] is used to forecast the mortality of patients. Fine et al. [21] proposed a rule to accurately identify the patients with pneumonia who are at low risk for death and other adverse outcomes. Pereira [22] tried to investigate association with clinical signs of pneumonia in children and predict the diagnosis by fuzzy sets theory. Statistical and machine learning techniques were investigated to predict the outcomes of patients with community acquired pneumonia [23,24]. Furthermore, artificial neural networks (ANN) have been used to predict the presence or absence of pneumonia among patients arriving at the emergency department with acute respiratory complaints. The results acquired with the use of ANN were analytically compared with those obtained using logistic regression modeling [23]. The same authors [25] proposed the use of genetic algorithms for neural networks to predict community-acquired pneumonia.

The above-mentioned solutions are able to implicate and analyze the data predicting the outcomes. But they are not able to describe the relationship among decision variables, which in most cases, have a qualitative nature. Recently, FCM approach was used to model the decision making problem of severity assessment of pulmonary infections [26]. The FCM technique was investigated to model the causality inherent in medical knowledge using experts' knowledge and clinical guidelines thus giving a front-end decision about the level of severity of pulmonary infections.

3. Overview of the fuzzy cognitive maps theory

Fuzzy cognitive map is a graph-based knowledge representation method that was proposed by Kosko [1] with the intention to represent causal relationships among concepts. The concepts and the causal dependencies between them were formalized [1] with the use of fuzzy set theory [27]. According to Kosko, the concept c_i is understood as a fuzzy union: $c_i = q_i \cup \neg q_i$, where q_i is a fuzzy set and $\neg q_i$ is its complement. The causal relationship was defined [1] for a pair of fuzzy concepts c_i and c_j. The positive causal relationship $c_i \xrightarrow{+} c_j$ holds if $q_i \subset q_j$ and $\neg q_i \subset \neg q_j$, where $\subset$ denotes a fuzzy implication. The negative causality $c_i \xrightarrow{-} c_j$ was defined as $c_i \xrightarrow{+} \neg c_j$. The definition of causal relationship led to the proposition of causal algebra expressed in terms of fuzzy operators. In consequence, the proposed FCM model is enabled [28] to perform reasoning that is based on numerical computations.

For the purpose of this paper, FCM is defined as an order pair $<C,W>$, where C is the set of labels and W is the quadratic connection matrix. Every label $c_i \in C$ is mapped to its activation value $a_i \in [0,1]$, where 0 means no activation and 1 means full activation. The labels from C can be interpreted as linguistic terms [2] that point to fuzzy sets. In such case, the activation value a_i is interpreted as the value of fuzzy membership function that measures the degree in which an observed value of the variable belongs to the fuzzy set pointed by the related term. The other, simplified interpretation of C, can be such that the labels c_i denote the corresponding real valued variables that are normalized into the $[0,1]$ interval. The latter, simplified interpretation of concepts, is applied by many researchers [5,29] and does not influence the computational methods that stand behind the reasoning process based on FCM.

The binary causal relationship within the set C will be represented by the matrix W. The matrix W does not change in time and stores the weights assigned to the pairs of concepts. The weights represent the generalized (over a given period of time) causal dependency between the concepts. The weights assume the values $w_{ij} \in [-1,1]$, where the value of weight $w_{ij} = 1$ expresses the full positive and $w_{ij} = -1$ full negative impact of ith causal-concept on jth effect-concept, respectively. The intermediate values of weight refer to partial causality.

At some time step t, the state of FCM is described by the activation values of its concepts. The activation values $a_i(t)$ of concepts constitute the state vector $A(t)$ of the FCM. The initial state of the FCM is usually computed on the basis of some observations (measurements). Then the reasoning process starts that aims at the prediction of future state of FCM.