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The methodology of Dynamic Uncertain Causality Graph for intelligent diagnosis of vertigo

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ABSTRACT

Vertigo is a common complaint with many potential causes involving otology, neurology and general medicine, and it is fairly difficult to distinguish the vertiginous disorders from each other accurately even for experienced physicians. Based on comprehensive investigations to relevant characteristics of vertigo, we propose a diagnostic modeling and reasoning methodology using Dynamic Uncertain Causality Graph. The symptoms, signs, findings of examinations, medical histories, etiology and pathogenesis, and so on, are incorporated in the diagnostic model. A modularized modeling scheme is presented to reduce the difficulty in model construction, providing multiple perspectives and arbitrary granularity for disease causality representations. We resort to the "chaining" inference algorithm and weighted logic operation mechanism, which guarantee the exactness and efficiency of diagnostic reasoning under situations of incomplete and uncertain information. Moreover, the causal insights into underlying interactions among diseases and symptoms intuitively demonstrate the reasoning process in a graphical manner. These solutions make the conclusions and advices more explicable and convincing, further increasing the objectivity of clinical decision-making. Verification experiments and empirical evaluations are performed with clinical vertigo cases. The results reveal that, even with incomplete observations, this methodology achieves encouraging diagnostic accuracy and effectiveness. This study provides a promising assistance tool for physicians in diagnosis of vertigo.

1. Introduction

In recent years, computational diagnostic tools and artificial intelligence techniques have been a subject of tremendous interests in the biomedical community for offering promise in improving the sensitivity and specificity of disease detection, diagnosis and prognosis. Take intelligent diagnosis, for instance, it can aid physicians in improving diagnostic accuracy across a wide range of medical specialties by quantifying important clinical indicators for diagnosis. Moreover, intelligent diagnosis approaches have the potential to cover some rare situations within a specialist domain, while no clinical expert can be expected to possess so encyclopedic knowledge of disease manifestations like that. Therefore, the application of intelligent diagnosis contributes to improve the quality of healthcare delivery.

The development and utilization of intelligent diagnosis methods have been involved in a wide range of medical fields. For example, in the diagnosis of Alzheimer's disease,

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Pinheiro et al. constructed a multi-criteria model based on Bayesian network to assist diagnoses [1]; Ramirez et al. presented a system aiming at detecting Alzheimer's disease in its early stage using support vector machine (SVM) classifier and classification tree [2]. For the diagnosis of heart valve diseases, Sengur investigated an ensemble learning methodology involving bagging, boosting and random subspace [3]; Avci et al. developed an intelligent system based on genetic-SVM approach, through dealing with combination of the feature extraction and classification from measured Doppler waveforms of heart valve [4]; Abdulkadir et al. made use of linear discriminant analysis and adaptive neuro-fuzzy inference system to determine the normal or abnormal heart valves [5]; A discrete hidden Markov model based diagnostic method was developed in [6], in which the algorithms of Discrete Fourier Transform and principal component analysis were respectively used for feature extraction and reduction from heart sound signals; Maglogiannis et al. developed an automated diagnosis system for the identification of heart valve diseases by SVM classification to heart sounds [7]. For breast cancer diagnosis, a feature selection technique named genetic programming was applied in the classification of breast masses in mammograms [8]; The breast cancer diagnosis system presented in [9] was based on fuzzy logic and genetic algorithm (FL-GA); A fuzzy association rule approach was proposed in [10] to automatically identify potential associations and biomarkers among main prognostic factors in breast cancer and whole-genome microarray data. For the diagnosis of liver disease, Rong constructed a diagnosis model which integrated artificial neural network (ANN), analytic hierarchy process and case-based reasoning method to distinguish between healthy and diseased livers and determine the type of liver disease [11]; A hepatitis disease diagnosis method based on SVM and simulated annealing was presented in [12]. Besides, Daliri et al. proposed a hybrid automatic diagnosis system for the lung cancer using GA and fuzzy extreme learning machines [13]. Polat et al. proposed a hybrid approach of feature selection, fuzzy weighted pre-processing and artificial immune recognition system to support medical decision-making [14]. Hamada et al. presented the architecture of a disease diagnosing system combining ANN, FL and GA to analyze images and identify abnormalities in disease diagnosis [15]. Chang et al. developed a hybrid model for medical data classification by integrating a case-based reasoning approach and particle swarm optimization algorithm [16]. Zhang proposed a multi-dimensional clustering method named as Latent Tree Model, which was applied to explore the statistical justification for syndrome differentiation [17] in traditional Chinese medicine.

Vertigo is one of the most common complaints in medicine, affecting approximately 20–30% of the general population at any age [18]. It refers to an erroneous perception of motion that is the result of mismatch between vestibular, visual, and somatosensory systems. Patients often present to primary care offices, emergency departments, and specialized dizzy clinics, for consultations. Because vertigo is the principal symptom in most of the otoneurological disorders having also other similar symptoms and its etiology is associated with otology, neurology and general medicine, it is difficult to separate vertiginous disorders from each other. Approximately 30% of the causes are unclear so far [18,19]. Most often, a definite diagnose on some kinds of vertigo diseases is almost impossible during a first visit, and surveys revealed that some patients have even visited physicians for more than five times. Some rare diseases tend to be ignored by general practitioners [19,20]. In order to provide physicians with assistance during the decision-making process [21], several otoneurological expert systems for the diagnosis and classification of vertigo have been developed. Mira et al. designed an automactic diagnosis system for dizziness (named as VERTIGO), which consisted of three modules including rules, findings and hypotheses [22]. Another expert system named as Carnisel was developed by Gavilan et al. for diagnosis of vestibular disorders [23]. It took two steps to make a diagnosis, first recommending the probable disease by analyzing patient's histories, then confirming the diagnosis by inputs of clinical examinations. Several computer specialists and otoneurologists in Finland have developed the otoneurological expert system (ONE) [24,25] to support diagnostics of vertigo. Its inference mechanism resembles pattern recognition methods, such as the weighted k-nearest neighbor, GA, FL and decision trees in the reasoning process based on the weight and fitness values set for attributes, which are referred to as the knowledge of the system. Clinical data with 38 initial attributes (now the number of attributes has been expanded to 94) concerning symptoms, medical history, and findings in otoneurologic, audiologic and imaging tests were collected at Helsinki University Hospital and incorporated in ONE. To classify the otoneurological diseases, a Bayesian probabilistic model was established by Miettinen et al. with a dataset regarding 6 diseases [26]. Refs. [27,28] presented the classification performance of ONE and other machine learning methods, such as k-nearest neighbor method (k-NN), Naïve Bayesian (NB) classifier and SVM on data of vertigo diseases.

Overall, the above intelligent diagnosis methods provide quantitative models and automated procedures for disease judgment by interpreting complicated clinical evidence with which the clinician is confronted. However, the early promise of these methodologies has resulted in only limited clinical utility [29]. Problematic with them, firstly, is the difficulty in understanding how such models construct the desired mapping function from input (e.g., medical data) to output (e.g., diagnosis). In particular, one must consider merging the interpretation of the diagnosis system with that of the physicians in clinical medicine because in most cases, diagnosis systems are seen as adjunctive after all. The implicit representation to etiology and pathogenesis reduces the persuasion of outcomes from diagnosis systems and consequently hinders the effective popularization of intelligent diagnosis technologies. Secondly, many data-driven methods solely resort to means of learning in model selection and parameter determination, which are difficult to model the underlying pathogenesis and pathophysiology characterized by individual differences and uncertain factors. Furthermore, the dependence on sampling data makes these systems incapable of functioning once the input information is incomplete and thus the diagnosis has to be doubted or left unconfirmed in many cases. Lastly, some diagnostic expert systems are very time consuming to be constructed, and diagnostic reasoning efficiency is also a matter of