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Intelligent ensemble T–S fuzzy neural networks with RCDPSO_DM optimization for effective handling of complex clinical pathway variances

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ABSTRACT

Takagi–Sugeno (T–S) fuzzy neural networks (FNNs) can be used to handle complex, fuzzy, uncertain clinical pathway (CP) variances. However, there are many drawbacks, such as slow training rate, propensity to become trapped in a local minimum and poor ability to perform a global search. In order to improve overall performance of variance handling by T–S FNNs, a new CP variance handling method is proposed in this study. It is based on random cooperative decomposing particle swarm optimization with double mutation mechanism (RCDPSO_DM) for T–S FNNs. Moreover, the proposed integrated learning algorithm, combining the RCDPSO_DM algorithm with a Kalman filtering algorithm, is applied to optimize antecedent and consequent parameters of constructed T–S FNNs. Then, a multi-swarm cooperative immigrating particle swarm algorithm ensemble method is used for intelligent ensemble T–S FNNs with RCDPSO_DM optimization to further improve stability and accuracy of CP variance handling. Finally, two case studies on liver and kidney poisoning variances in osteosarcoma preoperative chemotherapy are used to validate the proposed method. The result demonstrates that intelligent ensemble T–S FNNs based on the RCDPSO_DM achieves superior performances, in terms of stability, efficiency, precision and generalizability, over PSO ensemble of all T–S FNNs with RCDPSO_DM optimization, single T–S FNNs with RCDPSO_DM optimization, standard T–S FNNs, standard Mamdani FNNs and T–S FNNs based on other algorithms (cooperative particle swarm optimization and particle swarm optimization) for CP variance handling. Therefore, it makes CP variance handling more effective.

1. Introduction

Given an increasingly diverse set of health demands, clinical pathways (CPs) have been accepted as an important tool to facilitate the delivery of high-quality, low-cost, and customized healthcare services.

CPs are standardized, multidisciplinary management plans that display goals for patients and identify the appropriate sequence and timing of clinical interventions, milestones and expected outcomes to achieve these goals with optimal efficiency [1,2]. There are many definitions for CPs from origin to now. They have been implemented in many countries all over the world. In China, the Ministry of Health (MOH) launched to initially select 50 hospitals to implement CPs from 2009. At present, over 200 CPs have been implemented in more than 1300 hospitals across 30 provinces in China. Many references have reported that effective implementations CPs can reduce medical expenses, maximize clinical efficiency, increase patient satisfaction, improve the quality of medical care, and others [3–7].

CPs predefine a predictable standardized care process through collaborating of clinicians, nurses and other healthcare professionals for a particular diagnosis or procedure to improve the quality of patient care and reduce the medical cost. However, many variances may still be unavoidable due to individual complexities, the diversities and variability of diseases, and subjective initiatives carried out relating to patients or families, clinicians or nurses, hospital or system etc. during the execution process of CP. For example, some variances (like red and white blood cells decreasing, liver and kidney damages, platelets decreasing, stomatitis, neuropathy, etc.) occur usually during the execution process of osteosarcoma preoperative chemotherapy CP [8–10]. Moreover, most variances present complex, fuzzy, uncertain and high-risk characteristics, thus could cause complications or even endanger a patient's life if not handled effectively. Especially, standardization predefined CP models cannot provide suitable runtime support and appropriate decision-making for

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variances handling. Therefore, it is necessary to propose a new method to handle these variances accurately and effectively. However, recent research has mainly focused on documentation, classifying and analyzing the variances that occur during the implementation of CPs, e.g., [11,12], emphasizing the importance and difficulty for collecting, analyzing variance data. The handling of fuzzy and uncertain variances has seldom been considered. Therefore, we adopt the fuzzy rule-based reasoning method to handle CPs variances [10]. However, this method depends on the fuzzy rules provided by experts, which are usually difficult to obtain. Moreover, it lacks good adaptive learning abilities.

For several decades, Fuzzy neural networks (FNNs) have attracted many attentions and have been applied in many domains (such as medical diagnosis, image processing, pattern recognition and so on), which capture the benefits of fuzzy logic, in disposing vague and uncertain information associated with human cognition, and neural networks with good learning abilities [13–18]. In addition, many researchers [19–21] have found that the T–S fuzzy model can be more economical in network sizes (the number of input fuzzy sets and fuzzy rules) and learning accuracy than the general Mamdani-type fuzzy model.

According to characteristics of CP variances, T–S FNNs can be used for variance handling in this context, with an aim of assisting doctors in making diagnoses and handling decisions. Moreover, accuracy and efficiency of variance handling for CPs are crucial important. However, there are many drawbacks when performing T–S FNNs with a commonly-used back propagation (BP) algorithm with gradient descent for training [22], such as the propensity to be trapped in a local minimum, sensitivity to initial values, and poor ability in global searching. Genetic algorithms (GAs) can, on the other hand, be performed to fine-tune the obtained parameter set of premise parts and consequent parts in the FNN model. For example, an evolving method for the hierarchical T–S fuzzy model was proposed by Chen et al. [23]. A hybrid of a GA and a Kalman filter [24], a multi-objective hierarchical GA [25], has been proposed to optimize fuzzy models. These methods can attain better performance than BP algorithm in training T–S FNNs. However, the GA is characterized by huge computation time and slow convergence near the optimum [26].

Recently, a new evolutionary technique, particle swarm optimization (PSO) [27], has emerged as an important optimization technique [28,29]. Compared with GA, PSO has some attractive characteristics. It encourages constructive cooperation and information sharing between particles, which enhance search for a global optimal solution. Successful applications of PSO to various optimization problems, such as function minimization and T–S FNN design, have demonstrated their potentials [27,30]. A framework for identifying fuzzy models using PSO algorithm was proposed by Khosla et al. [31], and literature [32] compared PSO with GA for identifying fuzzy models with the same complexity generated from the same data.

Although many studies have shown that PSO performs well at global searching, easy to implement et al., it is relatively inefficient at performing local searches and is easy to be trapped in local optima. Shi and Eberhart [33] developed a parameter which they termed 'inertia weight' into the PSO, which was used to balance global exploration with local exploitation. Ratnaweera et al. [34] further developed the PSO, including time-varying acceleration coefficients to modify its local and global search ability and improving its performance through a random perturbation. Lovbjerg et al. [35] adopted the concepts of "subpopulation" and "breeding" to increase the population diversity. Xie et al. [36] developed a self-organizing PSO and improved the diversity by introducing negative entropy. He et al. [37] adopted an escaping operator on the velocity to ensure that particles would escape from the local optimum.

The above-mentioned techniques improve the global ability of the PSO to some extent, but it is still difficult to achieve a good trade-off between global convergence and convergent efficiency. Combining the PSO with notion of co-evolution, Bergh and Engelbrecht [38] proposed a cooperative particle swarm optimization (CPSO) algorithm which showed more effective than the traditional PSO in most optimization problems. A multi-swarm CPSO algorithm was used to optimize the parameters of a fuzzy model with fixed structure for dynamic systems processing [39]. However, when used with a simple splitting and collaborating approach, the CPSO algorithm may become trapped in sub-optimal locations in a search space. The sequence of the subgroup optimization can influence the optimization result. Especially, if the solution vectors are roughly split into several smaller vectors in order to decrease the computing time, however, not every parameter in the n-dimensional vector will be optimized sufficiently by this method. Many researchers have adopted random perturbation and existent mutation mechanisms, e.g., that in [40], to avoid the comparative inefficiency of the CPSO in fine-tuning the solution. However, this problem cannot be resolved radically.

In our previous study [41], we have proposed a subgroup decomposing mechanism for the particles during random cooperative evolution process. Although this method can improve the optimization performance to a certain extent, the problem with its premature convergence and low precision has not been solved completely. We extended our research to further improve the precision and avoid the comparative inefficiency of the CPSO in fine-tuning the solution. We obtained better solutions than those would be provided by the CPSO algorithm alone by means of double "mutation mechanism" once the CPSO has completed a predefined number of iteration cycles. This method is different from the existing ones, including ours previously. It increases the diversity of the swarms, offers guidance to the optimization by combining the current personal information with the best personal history information of the particles and improves searching ability so as to escape from a local optimum. The method is named random cooperative decomposing particle swarm optimization algorithm with double mutation mechanism (RCDPSO_DM).

Especially, the RCDPSO_DM algorithm not only allows "large" mutation ("pervasion mutation") but also "small" mutation ("exponential smoothing with simulated annealing mutation") to find a better solution. With combination of "large mutation" and "small mutation", the algorithm performance can be improved greatly. That is: (1) implementing large mutations helps the RCDPSO_DM escape from local optima (if necessary) and (2) carrying out a local search through small mutations helps to further improve the quality of the solutions found by the RCDPSO_DM. Variances in clinical pathway can result in complex, fuzzy, uncertain and high-risk characteristics. Therefore, the clinical pathways' variances need to be handled timely, effectively and accurately to avoid cause complicating diseases or even endanger patients' life.

In order to further improve the efficiency, precision and generalizability of T–S FNNs for the variance handling of CPs, we employ T–S FNNs with the RCDPSO_DM. However, the single T–S FNN with RCDPSO_DM has a poor stability. For variance handling of CPs, stability is very important for both doctors and patients. Therefore, this prompts us to find a new method to improve the stability.

The neural network ensemble is a finite collection of neural networks that are all trained for the same task. First the ensemble networks are independently trained, and following this step, their predictions are combined [42].

Most previous studies show that the neural network ensemble can significantly improve the generalizability and prediction accuracy of a neural network system. Moreover, the concept has already been applied successfully in many diverse areas [43–45], such as medical diagnosis, seismic signal classification, and others.