Indian Journal of Science and Technology, *Vol 8(15), 64743, July 2015*
ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Classification of Preterm Birth with Optimized Rules by Mutating the Cognitive Knowledge of PSO

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Abstract

Background/Objectives: Classification of preterm birth is a major challenge in the absence of effective tools and lack of domain knowledge with minimized set of rules. Objective of this paper is to classify the preterm birth with optimized rules. **Methods/Statistical Analysis:** This paper, proposes mutated Particle Swarm Optimization in order to achieve better result. Cognitive component was obtained by applying the mutation technique followed in the evolutionary algorithm. Mutation phase helped in converging to the optimized solution much faster. **Findings:** Preterm dataset of 1052 records with 5 attributes was applied to the proposed algorithm. Mutation was applied based on the Poisson, Gaussian, Uniform and Exponential distributions. The result shows that Poisson mutation among other distributions applied on the personal best has reduced the number of rules needed for classifying preterm birth datasets for both training and testing. It was observed that the optimized 13 rules out of 28 for training dataset and 9 rules out of 28 rules wereonly needed for classification. **Application/Improvements:** The proposed algorithm was suitable for preterm birth data set. This can be applied on the dataset with medium initial population. It was observed thatthe efficiency of the algorithm varied depends on the type of data. Therefore a generic method can be developed.

Keywords: Classification, Mutation, Particle Swarm Optimization, Pattern, Preterm Birth

1. Introduction

Preterm birth is a common occurring phenomenon in giving birth to pre mature babies. Birth of normal babies occurs in between 37 and 42 weeks of Last Menstrual Period (LMP) date. The babies born before the above period are termed as pre term child. About 70–80% of all neonatal deaths are due to the preterm delivery babies[1]. The research has been undergoing in identifying the cause for pre–term babies all over the world. The specific cause for the onset of labor pain[2] is still a greatest mystery in medicinal world. The infectious, nutritional status, socio–demography and psychological stress are the various causes for preterm birth[2]. Obstetric complications[3] like convulsions, bleeding, multiple gestations and hypertensions are some of the high risk factors for causing preterm birth. Consumption of liquid, caffeine, smoking cigarettes and weather related variationsare also some causes in preterm[1–3].

Particle Swarm Optimization technique was applied to evaluate the most optimized result from a domain of solutions. Each solution in the solution domain was considered as a particle which represents as one of the possible solution. Particle Swarm Optimization approach follows the concept of social behaviorism[4] of animals in tracking down for food. The animals share their finding knowledge related to other organisms in the group which will turn speed up the process of reaching the

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target food. The particles on their journey pass through intermediate positions which will change the course of direction of the particles and helps in reaching the target. The intermediate positions are reached by the particles by using the cognitive knowledge and social knowledge. Cognitive Knowledge[5–8] is the personal experience of the particle stored in the form of personal best position enjoyed by the particle from the initial position till the current position of the particle. The personal best of the particle will dynamically vary based on the new position if the fitness[9,10] of the new position is better than the existing personal best position. Social knowledge is the sharing of knowledge from the other members of the group which is passed on to the individual. Two types of knowledge sharing namely global best, where a leader is sharing the knowledge and a group of neighbors sharing the knowledge in the case of local best. In Global best PSO the best of best individual's knowledge is used for social component and varies dynamically in each iteration. In Local best PSO approach social knowledge was shared between a small neighborhoods[11] which was determined by different types of network structure.

Evolutionary[12] algorithmic approach was applied in iterating from generation to generation in fine tuning the pattern to be extracted which was hidden in the data sets. Evolutionary algorithm relies on the concept of chromosomes undergoing changes as generation progresses. The exchange of genetic material takes place between the parent chromosomes. There are two type of evolution namely phenotype and genotype. In genotype approach evolution of new generation takes place by exchange of genetic material between the parents to produce the offspring[12]. In phenotype approach a new offspring is obtained from each individual using the concept of mutation based on the adaptability of the environment. The Patterns are extracted in the form of rules[13] from the set of best particles in the swarm.

2. Methodology

Particle Swarm Optimization algorithm was applied on the pre–term dataset with the variation on the cognitive component of the velocity which undergoes mutation based on the environment. The Gaussian mutation was applied on the personal best of every individual and gets modified based on the environment. New Position of the particle at every iteration was obtained from the current position using the formula

$$P_i(t+1) = p_i(t) + V_{ij}(t+1) \qquad (1)$$

Where $P_i(t)$ is the current position of the particle represented in m dimensional solution space and $V_{ij}(t+1)$ is the new velocity of the particle. The velocity of the particle is obtained by modifying the current velocity with cognitive component and social component of the velocity.

$$V_{ij}(t+1) = v_{ij}(t)+k_1r_{1j}(y_{ij}-p_{ij})+k_2r_{2j}(y^\wedge_j(t)-p_{ij}(t)) \qquad (2)$$

Where $V_{ij}(t)$ is the inertia at the moment, y_{ij} is the personal best of individual particle iand y^ is the global best of the current population. The personal best of each individual is calculated using the given formula

$$Y_i(t+1) = \begin{cases} P_i(t+1) & \text{if } f(p_i(t+1) < f(y_i(t) \\ Y_i(t) \quad \text{otherwise} \end{cases} \qquad (3)$$

Where $P_i(t+1)$ is the new position, $f(P_i(t+1))$ was the fitness of the new position and $f(y_i(t))$ was the fitness of the previous personal best.The global best particle was the social component which contributes for the sharing of knowledge among the individuals. Global best position was obtained from the following equation as

$$Y^\wedge(t+1) = \begin{cases} y_i(t) & \text{if } \min\{f(y_i(t)) < f(y^\wedge(t))\} \\ Y^\wedge(t) & \text{otherwise} \end{cases} \qquad (4)$$

The course of direction of particles was derived from the deviation of the current direction from the cognitive component and social component of velocity.

The proposed algorithm where hybridization of the particle swarms optimization with the differential evolution is applied using various probability distributions under mutation. The pseudo code of the proposed algorithm is given in Figure 1 where the mutation function is performed with Poisson, Gaussian, Uniform and Exponential probabilistic distributions.

```
Mutated_personal_best_PSO ()

{Initialize a group of swarm particles of ns individuals of m dimensions;

While(!terminate Condition())

{ for each particle of the swarm

        { If(f(p_i(t) )  <  f(y_i(t))

                Y_i(t+1) = p_i(t);

                Y_i(t+1) = Mutation(y_i(t+1));

                If(f(y_i(t+1) < f(y^(t+1)))

                        Y^(t+1) = y_i(t); }

        for each particle of the swarm

        { Update the new velocity V_ij(t+1) using the equation  2;

        Update the new position p_i(t+1) using the equation 1; }

t=t+1; }
```

Figure 1. Pseudo code for Mutated personal best Particle Swarm Optimization.

Initially a group of swarms are generated by using random numbers based on the given data sets. The given data set is normalized between the intervals (0,1). The normalized data set is used for training the particle of swarm for reaching the target of expected optimized pattern for classifying the pre–term birth dataset. The terminate state is stopping after reaching some r iterations. In each iteration the personal best of every individual is obtained using the equation 3. Obtained personal best undergoes slight variation based on various Mutation techniques based on the environment to improve on the exploration prospects of the particles cognitive knowledge by randomly mutating some of the attributes. The mutation is given by

$$Y_{ij}(t+1) = y_{ij}(t)+ \Delta s \tag{5}$$

Where Δs is the mutated value of the cognitive component of the PSO. Gaussian Mutation is given by generating random number for few selected attributes using normal distribution between N(0,1).

$$Y_{ij}(t+1) = y_{ij}(t+1) + \mathrm{Normal}(0,1) \tag{6}$$

The Poisson Mutation is applied by generating a random number based on Poisson distribution for the personal best attributes based on the equation 7 where λ is the mean.

$$Y_{ij}(t+1) = y_{ij}(t+1) + \mathrm{Poisson}(\lambda) \tag{7}$$

The continuous Uniform mutation is applied by generating the Uniform distribution based on the following equation 8 where a is the lower limit and b is the upper limit.

$$Y_{ij}(t+1) = y_{ij}(t+1) + \mathrm{Uniform}(a,b) \tag{8}$$

The exponential mutation is performed by generating random number using exponential distribution specified in equation 9 where μ is the mean of the distribution

$$Y_{ij}(t+1) = y_{ij}(t+1) + \exp(\mu) \tag{9}$$

From the mutated personal best of every particle the global best is obtained by selecting the best personal best of the existing particles. After obtaining the personal best and global best of the particles, new velocity is obtained from the given equation 2 and new position is obtained from the equation 1. The decision support system[14] in the form of IF THEN rules are extracted from the set of best particles of the final population.

3. Experiments and Results

Experiments are conducted by collecting the preterm dataset of 1052 records each of five attributes and normal data set of 1314 records. Out of 1052 records 80% of the randomly selected records are used for training and remaining 20% records are used for testing. Normal datasets are used for validating the rules generated from the preterm datasets. After running the above proposed algorithm we are selecting the top 10% of best individuals and rules are generated from them by identifying the minimum and maximum values of each attribute. Rules are generated as follows

Rule 1: IF ($a_{1,min} < a_1$ && $a_{1,max} > a_1$) THEN class = pre–term.

Rule 2: IF ($a_{2,min} < a_2$ &&$a_{2,max} > a_2$) THEN class = pre–term.

Rule n: IF ($a_{1,min} < a_1$ &&$a_{1,max} > a_1$) AND ($a_{2,min} < a_2$ &&$a_{2,max} > a_2$) AND ……….AND ($a_{k,min} < a_k$ &&$a_{k,max} > a_k$) THEN class = Pre–term.

Mutation is applied on the personal best of every particle position of the PSO to improve on the performance of classification and optimize the number of rules needed for classification of training and testing datasets. Gaussian, uniform, Poisson and exponential distributions are applied for mutation on every particles best position to minimize the number of rules.

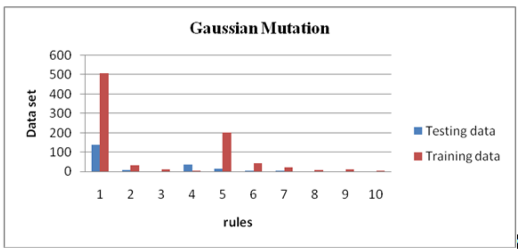

Figure 2. Satisfaction count of rules for testing and training datasets using Gaussian mutation.

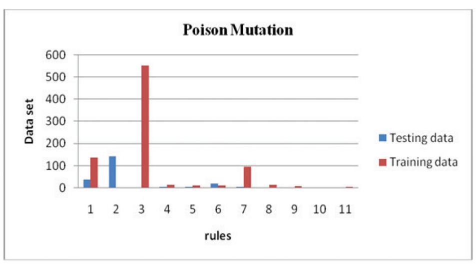

Figure 3. Satisfaction count of rules for testing and training datasets using Poisson mutation.

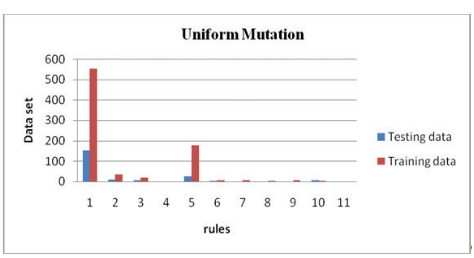

Figure 4. Satisfaction count of rules for testing and training datasets using Uniform mutation.

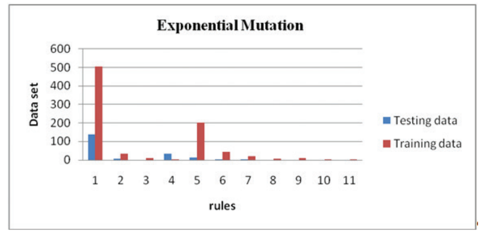

Figure 5. Satisfaction count of rules for testing and training datasets using Exponential mutation.

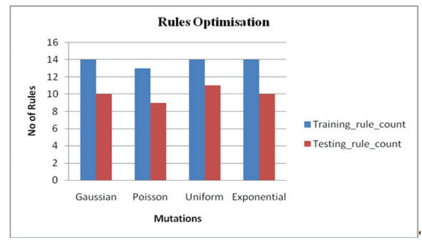

Figure 6. Comparison of various Mutation approaches in classification of preterm birth for training and testing data.

Figure 2 to Figure 5 shows the pattern of number of rules required for classification of preterm birth of training and testing datasetson applying mutations of various distributions. The Gaussian mutation requires 10 rules and 14 rules out of 29 rules for perform classifications for testing and training datasets. The Poisson Mutation requires 9 and 13 rules respectively for testing and training datasets. The uniform and exponential mutation requires 14 rules for training and 11 and 10 rules for testing data sets. Figure 6 shows the comparison of various mutation approaches in classifying training and testing data's of preterm datasets.

4. Conclusion

The research work of this paper mainly focused on applying the mutation approach of evolutionary algorithm in modifying the cognitive knowledge of each particle in PSO technique. The rules are optimized and faster convergence of iterations of swarm particles in extracting the pattern for classification is observed in the proposed muted PSO algorithm. The results show that Poisson mutation approach on the personal best has reduced the number of rules needed for classifying the preterm birth datasets for both training and testing datasets. The optimized 9 and 13 rules out of 28 rules are only needed for classification of testing and training datasets. The above work can be extended in varying the PSO with other evolutionary algorithms like Genetic Algorithm, Differential Evolution, Cultural Algorithm, and other social behaviorism algorithms like Ant colony, Bee Colony Optimization techniques.

5. References

1. Holcomb WL Jr, Smeltzer JS. Cervical effacement: Variation in belief among clinicians. Obstet Gyneco. 1991; 78:43–5.
2. Sonek JD, Iams JD, Blumenfeld M, Johnson F, Landon M, Gabbe S. Measurement of cervical length in pregnancy: Comparison between vaginal ultrasonography and digital examination. Obstet Gynecol. 1990; 76:172–5.
3. Catley C, Frize M, Walker CR, Petriu DC. Predicting High risk preterm birth using artificial neural networks. IEEE Transactions on Information Technology in Biomedicine. 2006 Jul; 10(3):540–9.
4. Zheng Y-J, Ling H-F, Xue J-Y, Chen S-Y. Population classification in fire evacuation: A multi objective Particle Swarm Optimization Approach. IEEE Transactions on Evolutionary Computation. 2014 Feb; 18(1):70–81.
5. Campos M, Krohling RA, Enriquez I. Bare bones Particle Swarm Optimization with scale matrix adaptation. IEEE Transactions on Cybernetics. 2014 Sep; 44(9):1567–78.
6. Kulkarni RV, Venayagamoorthy GK. Particle Swarm Optimization in Wireless Sensor Networks: A brief survey. IEEE Transactions on Systems, Man, and Cybernetics PART C: Applications and Reviews. 2011 Mar; 41(2):262–7.
7. Kiranyaz S, Ince T, Yildirim A, Gabbouj M. Fractional Particle Swarm Optimization Chung in Multidimensional Search Space. IEEE Transactions on Systems, Man, and Cybernetics - Part B: Cybernetics. 2010 Apr; 40(2):298–319.
8. Wang H, Zhang Y. Improvement of discrete Particle Swarm Classification System. 2011 Eighth International Conference on Fuzzy Systems and Knowledge Discovery (FSKD). 2011 Jul; 2:1027–31.
9. Toreini E, Mehrnejad M. Clustering Data with Particle Swarm Optimization using a new fitness. 2011 3rd Conference on Data Mining and Optimization (DMO). Selangor, Malaysia. 2011 Jun 28-29. p. 266–70.
10. Nikoul HR, Semsari M. Digital Circuit design using Chaotic Particle Swarm Optimization assisted by genetic algorithm. Indian Journal of Science and Technology. 2013 Sep; 6(9):5182–8.
11. Nagarajan E, George R. Enhanced one–to–many data Linkage. International Journal of Applied Engineering Research. 2015; 10(2):3411–6.
12. Zhong J–H, Shen M, Zhang J,Shu-Hung H, Shi Yu–Hui, Li Y. A Differential evolution algorithm with dual populations for solving periodic railway timetable scheduling problem. IEEE Transactions on Evolutionary Computation. 2013 Aug; 17(4):512–27.
13. Cohen WW. Fast effective rule induction. Proceedings of 12th Conference on Machine Learning (ML'95).
14. Nagarajan E, Sravani VS. Knowledge Abstraction from MIMIC 2nd using Apriori Algorithm for Clinical Decision Support System. Indian Journal of Science and Technology. 2015 Apr; 8(8):728–30.