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Article

Effect analysis of functional physical fitness training based on improved genetic algorithm under functional analysis

Danxu Lu

College of Physical Education, Hunan University of Science and Engineering, Yongzhou 425199, China; mangguowangqiu@163.com

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Abstract: In addition to helping athletes enhance their athletic abilities and spark their interest in sports, youth athletics amateur training can also set the groundwork for athletes' future athletic growth. Physical training still has less than optimal results for Chinese youth, nevertheless. The physical training effect of athletes can be maximized with the aid of amateur training. We can direct the creation of the most sensible physical training plan and choose the best physical training technique in order to achieve the ideal physical training goal and realize the steady improvement of athletes' physical fitness by focusing more on and analyzing the fundamental and unique physical training strategies. Therefore, in order to improve the scientific and state-of-the-art analysis of training effect and to provide more scientific guidance for youth physical training, this paper introduces scientific quantitative indexes and personalized customized indexes into physical training from the perspective of genetic algorithms.

Keywords: adolescent; amateur; physical training; functional fitness training; improved genetic algorithm

1. Introduction

Physical fitness training has always been a critical focus of physical education teaching. Historically, physical fitness training can be traced back to medical gymnastics in ancient Europe and daoyin practices in ancient China, which were originally applied in medical rehabilitation and therapy. Over time, with advancements in educational research, the scope of physical training expanded to include physical function training, which became increasingly integrated into educational frameworks [1]. In many developed countries, such as those in Europe and the United States, physical function training has evolved into comprehensive physical fitness programs characterized by mature training concepts and models. These programs emphasize enhancing athletes' physical literacy and are closely aligned with the principles of quality education and national fitness campaigns, which have also gained prominence in our country [2,3].

In China, amateur sports training programs have been extensively implemented in schools to promote physical fitness. These programs aim to optimize athletes' basic postures and movement patterns, ensuring their peak athletic ability and stable physical strength. For example, in youth amateur training, the proper introduction of moderate-intensity physical training is essential for improving physical fitness, enhancing exercises, and targeting small muscle groups to improve physical stability, flexibility, and coordination [4,5].

However, balancing training intensity and volume remains a major challenge in physical training. Studies indicate that for sprinters, reducing training intensity by 40%

can increase training volume by 14 to 15 times. While this allows athletes to achieve greater running distances, it often fails to yield breakthroughs in performance for specialized activities [6]. Similarly, for long-distance runners, increasing training volume excessively while reducing intensity can result in stagnation, preventing athletes from surpassing their current state and achieving the desired training outcomes. Conversely, increasing training intensity while reducing training volume can lead to heightened stress on the central nervous system and negatively impact the psychological state and overall health of athletes [7]. Thus, only through a scientific and reasonable approach to balancing training intensity and volume, tailored to specific athletic disciplines, can the best training outcomes be achieved.

To address these challenges and achieve the optimal balance between training intensity and volume, this paper introduces a genetic algorithm as a global optimization tool for youth amateur training [8]. By integrating scientific, quantitative, and customized indicators, this method provides a personalized training framework designed to improve athletes' physical fitness. While the algorithm demonstrates notable innovation in optimizing task scheduling and resource allocation in training, its adaptability to varying training scenarios warrants further discussion [9,10].

For instance, the genetic algorithm's effectiveness in different scenarios, such as training for sprinters versus long-distance runners, needs to be thoroughly analyzed. The adaptability of the algorithm to diverse conditions, including differences in age, gender, and athletic specialization, should also be considered [11,12]. Additionally, comparing the genetic algorithm to other optimization techniques, such as deep learning and reinforcement learning, could provide valuable insights into its relative strengths and weaknesses. Future research should focus on refining the algorithm to enhance its performance in specific applications and ensure its robustness across various training contexts.

By addressing these aspects, the genetic algorithm can be further optimized to provide scientifically grounded and highly adaptable solutions for improving physical training outcomes in youth amateur sports.

2. Related work

2.1. Analysis of training effect in youth amateur training

Theoretical guidance is the scientific basis for improving the training effect [13]. The experience of material selection can be sublimated into the scientific theory of material selection, and the scientific theory and scientific testing methods can evaluate or correct the material selection experience and complement each other. To a certain extent, accelerate the scientific selection of materials. The selection of modern athletes, based on scientific theories, combined with high-tech means and methods, carries out standardized procedures and steps: (1) conduct family investigation; (2) conduct physical examination; (3) conduct developmental degree and puberty developmental orgasm duration and Developmental type investigation; (4) to test the selection index; (5) to evaluate and analyze the test results. By testing and analyzing various physiological, biochemical, neurological, psychological and even genetic indicators of adolescents' form, function, and quality, the possible results of athletes can be predicted, so that the selection of materials can be continuously explored in terms of the depth, breadth and precision of indicators [14]. Special sensitive indicators are related to the rate of completion of athletes and the quality of finished materials. It mainly refers to the certain abilities that athletes have for the highest level of the special project. Coaches and scientific researchers design some special sensitive indicators according to the decisive factors of the project. Predict the future competitive ability of athletes [15]. In modern physical training, both general ability training for athletes and special ability training are emphasized. General ability is the basis of special ability and plays an indirect supporting role in sports performance. Advanced level must master advanced and reasonable special technology [16]. In the basic and primary training stages, general training occupies an important position. With the improvement of athletes' age and sports performance, the proportion of special ability training gradually increases until it enters the high-level stage, special training becomes the core of training [17]. For high-level athletes, more specialized exercises are arranged to make them more directly adapted to the needs of competition movements. The selection of special practice methods pays great attention to the principle of less but more refinement and optimization [18]. However, some coaches in the training do not have a deep and comprehensive understanding of the amount of exercise, and unilaterally pursue the number of training sessions, but the results are not good. Training theory and practice have proved that only by increasing the exercise load in the training process can the stimulation to the athlete's organism be deepened and the level of training adaptation be improved. In the process of increasing the amount of exercise, it is necessary to deal with the relationship between the amount and the intensity [19]. It is generally believed that heavy load training is suitable for athletes of any age and any level [20]. Generally, the load intensity of the period should be determined according to the characteristics of the project, the requirements of training and competition tasks, and then the number of load requirements should be arranged under the premise of ensuring the intensity requirements. Third, for high-level athletes, training to improve technique must also be performed in full form at higher intensities.

2.2. Genetic algorithm

During operation, many motion management systems schedule jobs one at a time. These motion flow management systems' dynamic techniques frequently only optimize the time it takes to complete a single activity, failing to take the motion flow system as a whole into consideration. It is optimized for the amount of time needed to complete every task [21]. Alcock et al. [22] suggested a genetic algorithm-based motion flow scheduling system, but its application was restricted because it ignored potential concurrency relationships between activities. In this paper, an improved genetic algorithm (IGA) is proposed to plan the task sequence and resource combination with the shortest execution time before the execution of the motion flow, so as to achieve the purpose of global optimization, and the order between tasks is considered in the chromosome encoding. and concurrency.

3. Methods

3.1. Modeling adaptation

According to the appropriate resource allocation principle proposed by Alcock et al. [22], it is necessary to make decisions on the task execution sequence and how to allocate resources. In this paper, these two decisions can be abstracted into two problems: task sequence and resource allocation.

Task Sequence and Resource Allocation $t(i = 1,2,...,m)$. It represents m tasks that need to be executed in the motion flow, and there may be constraints and concurrency between each task. The task sequence represents the task set composed of all tasks in the motion flow, but the sequence of tasks is not necessarily the same. Assuming that I can only be executed after I is executed, it means that t is a pre-order task of 0. When the pre-order tasks of multiple tasks are executed, and these tasks have no resource occupation conflicts, these tasks can be executed concurrently. It should be noted that the order of the task sequence does not represent the task execution order, it indicates that when resources conflict, A task t can be executed if and only if all tasks between L and t in the task sequence that are allocated the same resource as the task have been executed. In the task sequence, the pre-order task of Z cannot appear after one, otherwise it may cause a deadlock problem, which is an infeasible task sequence and cannot guarantee that the execution of the motion flow is completed. $RM = 1,2,...,n$ Represents n resources provided to the task execution needs. R_t represents the set of candidate resources that can complete task t, $RT_i$is a subset of R. When the task is running, it only needs to select any resource from R_t to complete the task. In this paper, it is assumed that each task uses different resources to complete the processing time can be different, a resource can be used by multiple tasks, but at the same time only one task can be occupied. When two tasks compete for the same resource at the same time, the task ahead in the task sequence has the priority to occupy the resource. Considering the above factors, different task sequences and different resource allocation will lead to different execution time of motion flow.

Optimization objective when the motion flow system has limited resources and tasks can run concurrently, the objective of IGA optimization, as proposed in this paper, is to determine the best combination of task sequence and resource allocation in order to reach the goal of the shortest time for motion flow to finish all tasks.

3.2. Using the improved genetic algorithm to make a scheduling scheme

The problem discussed in the nested genetic paper involves two sets of variables, task sequence and resource allocation. These two sets of variables affect each other. If each set of variables is optimized independently, the global optimal solution cannot be obtained, but the nested genetic algorithm can be used efficiently. It can overcome the shortage of standard Genetic Algorithm (Canonical Genetic Algorithm, CGA) by searching the entire solution space, so nested Genetic Algorithm is used in this paper. The algorithm is divided into two layers, the first layer determines the task sequence, and the second layer searches for the optimal resource allocation based on the known task sequence. In order to ensure the correctness and validity of sequence planning results, the concept of priority constraint matrix is introduced. PCM is an $M \times M$ matrix. The elements in the matrix represent the relationship between tasks. In the text, C is used to represent the priority restriction matrix, and i and i represent the row number and column number of the PCM matrix C. The value of represents the relationship between task i and task J.

$$C_{ij} = \begin{cases} 0 There\ is\ no\ sequential\ restriction\ between\ tasks\ I\ and\ j, which\ can\ be\ executed\ concurrently \\ 1 Task\ J\ can\ only\ be\ executed\ after\ task\ I\ is\ completed \\ -1 Task\ I\ can\ only\ be\ executed\ after\ task\ J\ is\ completed \end{cases} \quad (1)$$

Fitness function

$$F_{indi} = M_t - T_{indi} \quad (2)$$

$$M_t = \sum_{i=1}^{m\sum(T_{ij})(j=1,2,\ldots,n)} max \quad (3)$$

Fitness function F; the time required to execute task i, the sum of the longest time required to execute each task in a task sequence, M when the tasks and resources are known. The value is fixed and represents the time required for the individual to perform all tasks.

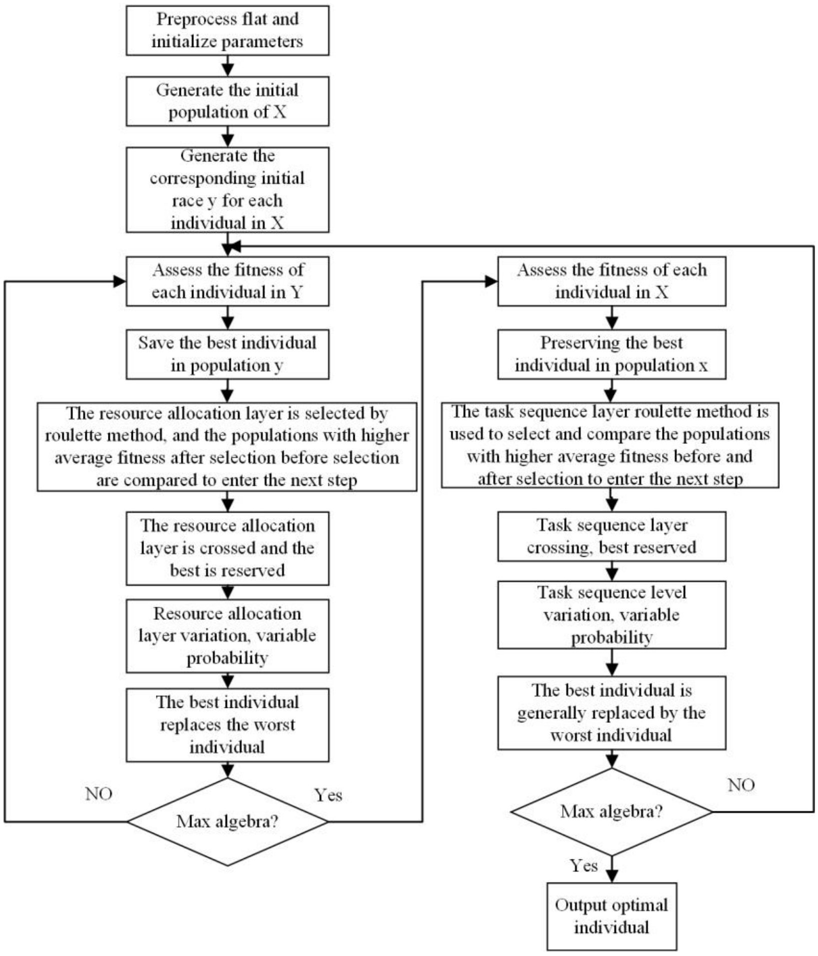

Figure 1. Flow chart of improved genetic algorithm.

Improved genetic algorithm flowchart. The variable x in **Figure 1** represents the task sequence layer, and the variable y represents the resource allocation layer. The algorithm is mainly divided into two layers: the task sequence layer and the resource allocation layer. The specific improved genetic operation details will be explained in detail below.

In the task sequence layer of chromosomal coding, viable task sequences are used to represent chromosomes. It is not necessary for tasks to be completed in order for a task sequence to be feasible. When all pre-order tasks have been finished, multiple tasks can be executed concurrently. However, when concurrent execution takes place, resource contention will dictate how resources are distributed according to the task sequence, but the resources in use cannot be preempted.

The initial population generation method randomly selects feasible task sequences to form the initial population. The elite retention operation and the improved selection operation first adopt the elite retention strategy Hu to retain the optimal individual, and then perform the selection operation. The selection operation adopts the roulette method, and the average fitness of the population before and after the selection is compared, and the best one enters the crossover operation. The improved selection operation can prevent the roulette method from selecting a population whose average fitness is not as good as before the selection to enter the crossover operation in the case of a small probability.

A better crossover operation that can guarantee the acquisition of lawful chromosomes following crossover is suggested by Wang [23] and is appropriate for the job sequence layer. This study proposes an intersection method that randomly chooses an intersection in front of two feasible task sequences. The matching area is the task sequence that lies between the first task in the task sequence and the task that the intersection points to. Assuming that the two task sequences are parent 1 and parent 2, respectively, create two intermediate task sequences by first adding the matching areas of parent 1 and parent 2 to the front of each other. Then, as illustrated in **Figure 2**, remove the same task as the matching area outside the matching area to create two child sequences. For more information, see **Figure 3**'s motion flow system. The child individual obtained through the above crossover process cannot be guaranteed to be feasible, so the feasibility of the child individual needs to be verified according to the PCM. If it is found to be infeasible, delete the first infeasible task and its subsequent tasks in the task sequence, and generate the remaining tasks according to the PCM to ensure the feasibility of the task sequence. In order to further promote the convergence of the algorithm, the fitness of the two parents and children is compared after the crossover. The two individuals with large fitness enter the mutation operation, and the individual with small fitness is eliminated.

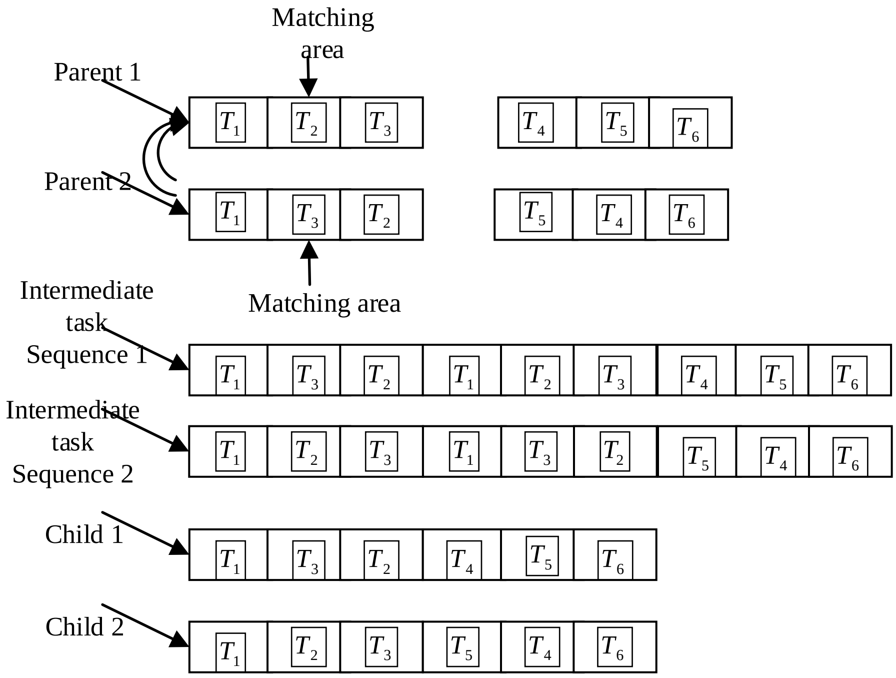

Figure 2. Improved crossover method.

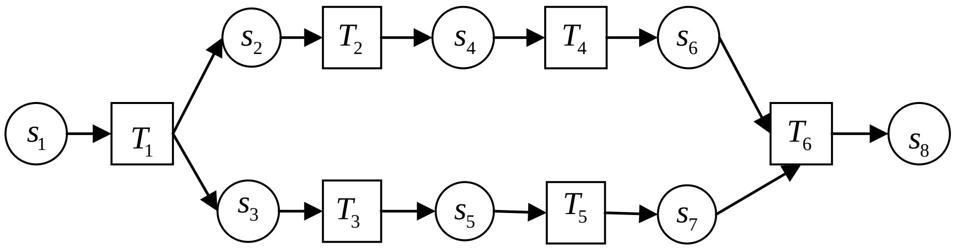

Figure 3. Example workflow system.

The improved mutation operation, because there may be a constraint relationship between tasks, needs to ensure the feasibility of the task sequence after mutation, so the mutation method of traditional genetic algorithm cannot be used for mutation [24]. First, a chromosome is randomly selected for mutation, a task I in the task sequence is randomly selected, and all tasks after task t in the task sequence are deleted. Since the use of PCM can ensure the feasibility of the task sequence, PCM is used to randomly plan new tasks according to the remaining tasks to form a new feasible task sequence to achieve the purpose of mutation [25]. In addition, because the elite retention strategy and the optimal strategy in the alternate method will lead to rapid convergence of the algorithm, the algorithm may converge to the local optimal solution. In order to make the algorithm search the entire solution space as much as possible, the variable mutation probability u is used in this paper to maintain population diversity.

The replace worst individual operation involves substituting the worst-performing individual in the mutated population with the best individual retained through the elite mechanism.

In the resource allocation layer, chromosomes are encoded using a resource sequence, where each resource sequence corresponds to a task sequence. This establishes a direct relationship between tasks and their allocated resources. Each resource sequence represents an individual in the resource allocation layer, with the resources within the sequence functioning as genes in the chromosome.

To generate the initial population, a random resource is assigned to each task based on the known task sequence, ensuring all selected resources are available for the task. The length of the resource sequence matches the length of the task sequence. A total of popSize resource sequences are selected to form the initial population, where popSize represents the population size.

The elite retention operation and the improved selection operation follow the same methods as those used in the mission sequence layer.

The crossover operation employs the traditional single-point crossover method, where a random crossover point is selected to perform the operation. Similarly, the mutation operation involves randomly selecting a mutation point in the chromosome and replacing the resource at that point with another resource randomly chosen from the set of resources capable of completing the corresponding task. The mutation probability changes dynamically, as in the mutation operation at the task sequence layer.

Finally, the replace worst individual operation ensures that the worst individual in the mutated population is replaced with the best individual retained by the elite, maintaining the quality of the population and driving optimization.

4. Experiments

4.1. Experimental environment and comparison method

The experimental hardware platform is a personal notebook computer, the CPU is InterDuo2.10 GHz, the memory is 2 GB, the software platform is WindowsXP2002, and the development tool is Myeclipse7.5. This paper will compare the time required to complete all tasks by using the dynamic method H'51, CGA and IGA methods in the same motion flow system under the same software and hardware environment, and the method with the shortest time is the best.

4.2. Experimental motion flow system and experimental data

Here, a simple motion flow system is used to describe the experimental process. The motion flow system here is described by a petri net, as shown in **Figure 3**.

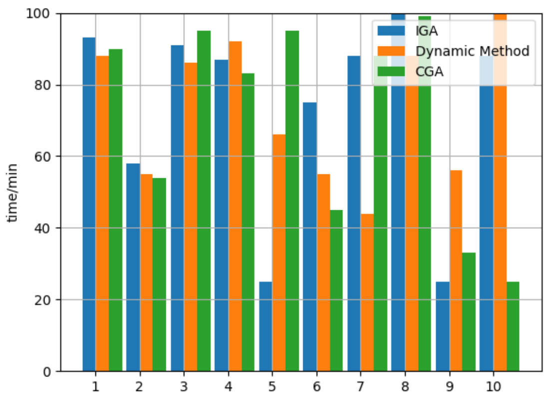

Figure 4. time comparison of IgA method, dynamic method and CGA method.

Set the relationship between tasks and resources, *t* represents task *i* represents resources. **Figure 4**. IGA method, dynamic method, CGA method time vs. task *i*, the relationship between tasks and resources are shown in **Table 1**.

Table 1. Task resource relationship.

$T_i \backslash T_{ij} \backslash R_j$	T_1	T_2	T_3	T_4	T_5	T_6
R_1	31	15	14	0	24	11
R_2	0	19	37	14	0	33
R_3	48	15	0	19	0	44
R_4	26	21	41	21	20	0

4.3. Experimental results using dynamic method

Motion Flow System Allocating Resources From the experimental results of this example, it can be concluded that using the IGA method can minimize the execution time of the entire motion flow. Subsequently, experiments were carried out with 9 other motion flow systems with different structures or motion flows with the same structure and different task-resource relationships, including motion flows with and without concurrent relationships. The experimental results are shown in **Figures 4** and **5**.

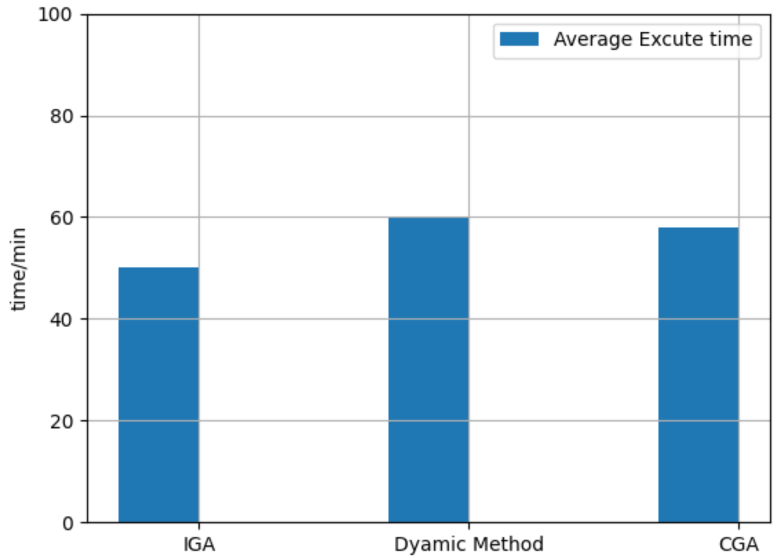

Figure 5. Comparison of average execution time of IgA method, dynamic method and CGA method.

When there are no concurrently executed tasks in the resource-constrained motion flow, the execution time of the IGA method and the dynamic method is the same and both are better than or equal to the CGA method, according to the experimental results. However, when there are concurrently executed tasks, the IGA method consistently outperformed or was on par with the other two methods in terms of execution time. Furthermore, it is possible to determine that the motion flow system employing the IGA approach has the shortest average execution time based on the average execution time of the motion flow instance in **Figure 5**.

5. Conclusion

This work proposes an IGA algorithm for global motion flow system optimization and compares it with motion flow systems based on the CGA and dynamic scheduling methods. Because the IGA algorithm can perform global optimization on the entire motion flow, as well as the search range and convergence, the experimental results demonstrate that using the IGA method will always result in a motion flow system that is better than or equal to using the dynamic scheduling method and the CGA method in terms of total time consumption, regardless of whether there are concurrent execution tasks. Only one task is optimized by the dynamic scheduling approach, and it is simple to get caught in a local optimum. Despite the fact that CGA optimizes motion flow worldwide as well, algorithm convergence cannot be guaranteed, and the final solution might not be the best one.

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

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