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On the optimization of multitasking process with multiplayer[☆]

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HIGHLIGHTS

- A model of multitasking process with multiplayer (MPM) is proposed.
- The random choice strategy is better than the shortest queue strategy.
- If an individual first processed the time-consuming task, he probably could spend less time in completing all the tasks.

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ABSTRACT

In society, many problems can be understood as multitasking process with multiplayer (MPM). Choosing different strategies or different orders in processing tasks, an individual will spend a different amount of time to complete all the tasks. Therefore, a good strategy or a good order can help an individual work more efficiently. In this paper, we propose a model to study the optimization problems of MPM. The average time spent for all the tasks by an individual is calculated in each strategy, and we find the random choice strategy can make an individual spend less time in completing all tasks. The correlation coefficient between the order of each task processed by an individual and the corresponding time spent for all the tasks by the individual is also calculated. Then the internal statistics law between the order and the corresponding time is found and explains why the random choice strategy is better. Finally, we research the change of the queue length in each task with the time. These results have certain significance on theory and practical application on MPM.

The research on the dynamics of human behavior has been getting increased attention in the field of complexity science. In the past decade, a lot of work has been done to give a deeper understanding of human behavior [1–11]. These works mainly focused on the temporal and spatial distribution characteristics of human activity patterns. Because of the complexity of human behavior, many underlying mechanisms have not been discovered yet. We should research human behavior with more other aspects to get broader and deeper cognizance. With the development of society, people always hope to get more

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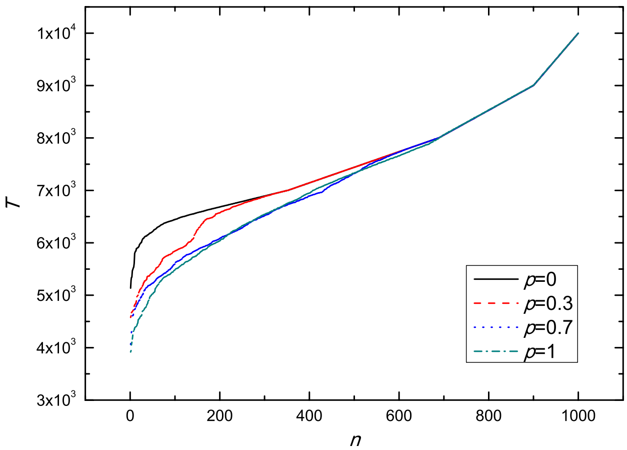

Fig. 1. The time T spent for all tasks by each individual. In order to facilitate the calculation and statistics, the parameters are assigned: $n = 1000$, $m = 100$, and $\tau_1 = 1$, $\tau_2 = 2$, $\tau_3 = 3, \ldots, \tau_{10} = 10$ unit times. n represents the number of each individual in the four sub-figures. The number n of each individual is from 1 to 1000, correspondingly, the time spent for all tasks by each individual is arranged from minimum to maximum. The black solid line, red dashed line, blue dotted line, dashed and dotted line represent the corresponding result in the case of $p = 0$, 0.3, 0.7, and 1, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

done in less time. Human-initiated systems always run in a complex way, so scientific management and time optimization are very important for human society. Multitasking process with multiplayer (MPM) is one of the complicated but common phenomena in daily life, such as physical check-up, for which each individual needs to complete all physical examination items of medical. There are some studies on a single-tasking process with multiplayer or multitasking process with a single-player [12–24]. But the study on MPM is, very few.

In this paper, we will present a model to study the optimization problems of MPM. Through simulation experiment and mathematical analysis, we research that which strategy is better and what is the intrinsic mechanism in the better strategy. These researches have certain significance on theory and practical application on MPM in reality. The outline of the paper is as follows. In Section 1, the MPM model will be presented. In Section 2, we show the simulation results of our model. In Section 3, we will summarize our works in this paper. The last part is our acknowledgments.

1. The model

Our model of MPM is stated as follows:

(i) there are n individuals and m tasks. All the tasks are numbered as $1, 2, 3, \ldots, m$. Correspondingly, the completion time of each task is $\tau_1, \tau_2, \tau_3, \ldots, \tau_m$ unit times. Each individual needs to complete all the m tasks. All individuals are independent of each other, and so are all the tasks;

(ii) in the beginning, all the individuals randomly choose one task. From the first time step, there are two alternative strategies for each individual to complete all the tasks. When an individual completed a task, the first strategy is that he will randomly choose a new one from the uncompleted tasks and the second strategy is that he will choose a new one with the shortest queue length among all the uncompleted tasks;

(iii) a fraction p of all the n individuals chooses the first strategy to process all tasks and the others choose the second strategy. In order to facilitate the simulation, we assume that 1 unit time is equal to 1 time step.

2. Simulation results and discussion

Fig. 1 shows the time spent for all tasks by an individual in the case of $p = 0$, 0.3, 0.7, and 1. The time is arranged from minimum to maximum. There is a minimum in each curve, and there are four minimums in the four curves. When $p = 0$, all the individuals choose the second strategy, and the minimum is the biggest in the four minimums. When $p = 1$, all the individuals choose the first strategy, and the minimum is the smallest in the four minimums. It is to say that the random choice strategy could make an individual spend less time in completing all the tasks than the shortest queue strategy. The maximum of each curve is equal to 10,000 time steps. The reason is that the most completion time of a single-tasking among 10 tasks is 10 unit times and there are 1000 individuals. Therefore, whichever strategy an individual chooses, the most time spent for all the tasks is $10 \times 1000 = 10{,}000$ time steps. What is more, the maximum is about twice as much as the minimum in each curve. No doubt, the gap between the maximum and minimum is quite obvious. If we can find the reason for the phenomenon, it must be of very important significance to optimize the running time of MPM in the model. In order to further understand the above findings, we need to do a more detailed study on the average time spent for all the tasks by an individual in each strategy.

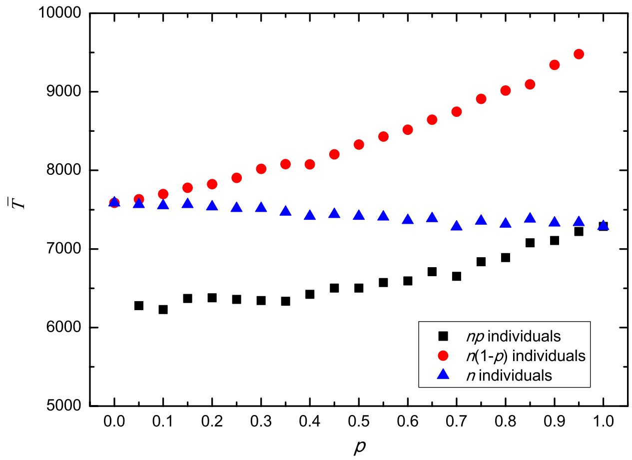

Fig. 2. (Color online) The average time $\overline{T}$ spent for all the tasks of an individual in each strategy. The parameter p is assigned from 0 to 1, and the step is 0.05, and the other parameters are the same with Fig. 1. The black squares represent the average time spent for all the tasks by an individual using the random choice strategy, and the red dots represent the average time spent for all tasks by an individual using the shortest queue strategy, and the blue up triangles represent the average time spent for all the individuals.

Fig. 2 shows the statistical law of the average time $\overline{T}$ spent for all the tasks by an individual in each strategy. The formula of calculating the average time is

$$\overline{T} = \frac{\sum_{i=1}^{N} T_i}{N}, \tag{1}$$

where T_i is the time spent for all the tasks by an individual, and N is the total number of samples. When the value of p is determined, we can find that the average time of the np individuals who choose the random choice strategy is much shorter than the one of the $n(1-p)$ individuals who choose the shortest queue strategy. This is very different from our common sense, because people generally think that the shortest queue strategy can make them to spend less time in completing all the tasks in daily life. With the increase of p, the average time for each strategy increases, while the average time of all the individuals decreases. The reason is that the larger the p is, the more the individuals of choosing the random choice strategy are. When $p = 0$, all the individuals choose the shortest queue strategy and the average time reaches to the maximum. When $p = 1$, all the individuals choose the random choice strategy and the average time reduces to the minimum. Therefore, if an individual changed the strategy from the shortest queue strategy to the random choice strategy, he probably could spend less time in completing all the tasks and the average time of all the individuals could also be shortened. This result is very interesting. We will make a deep research to discover the reason that the time spent for all tasks by an individual in the random choice strategy is less than that in the shortest queue strategy.

Fig. 3 shows the results of the correlation coefficient between the order of each task processed by an individual and the corresponding time spent for all tasks by the individual in the case of $p = 0, 0.3, 0.7$, and 1. The correlation coefficient is given by

$$\rho_{Z,T} = \frac{E(ZT) - E(Z)E(T)}{\sqrt{E(Z^2) - E^2(Z)}\sqrt{E(T^2) - E^2(T)}}, \tag{2}$$

where E is the mathematical expectation, and Z represents the order of each task processed by an individual, and T represents the corresponding time spent for all the tasks by the individual, so there are n sets of Z and T for each task, and $\rho_{Z,T}$ represents the correlation coefficient between Z and T. We can apparently find that if the number of a task is small ($m \le 5$), the correlation coefficient is negative, conversely when the number of a task is larger ($m \ge 8$), the correlation coefficient is positive. Because the smaller the number of a task is, the less the completion time of the task is; the larger the number of a task is, the more the completion time of the task is. Therefore, an individual that spends less time in completing all tasks generally first processed the time-consuming task and finally processed the less time-consuming task. Conversely, an individual that spends more time in completing all the tasks generally first processes the less time-consuming task and finally processes the time-consuming task. In other words, if an individual first processed the time-consuming task and finally processed the less time-consuming task, the individual may well spend shorter time in completing all the tasks. This result can explain the reason why the time spent for all tasks by an individual in the random choice strategy is less than that in the shortest queue strategy. This is because it is higher probability to let individual first process the time-consuming task in the random choice strategy than in the shortest queue strategy. Less time-consuming task is easier to be completed and the queue length in less time-consuming task generally is shorter. Therefore, after a task was completed, an individual

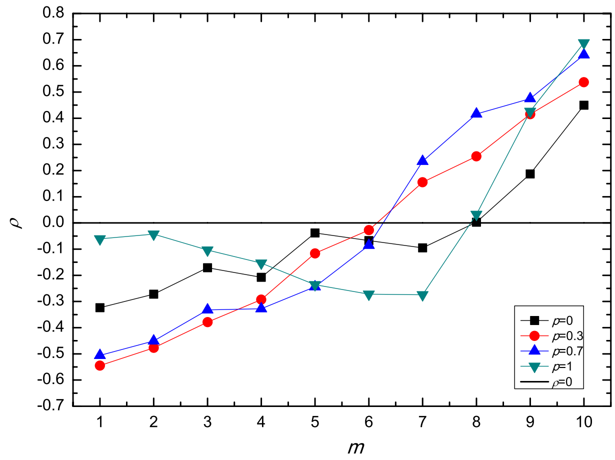

Fig. 3. (Color online) The correlation coefficient ρ between the order of a task processed by an individual and the corresponding time spent for all the tasks by the individual. The parameters are the same with Fig. 1. The abscissa m is the number of each task, and the ordinate ρ represents the correlation coefficient. The black squares, the red dots, the blue up triangles, the olive down triangles represent the corresponding results in the case of $p = 0, 0.3, 0.7$, and 1, respectively.

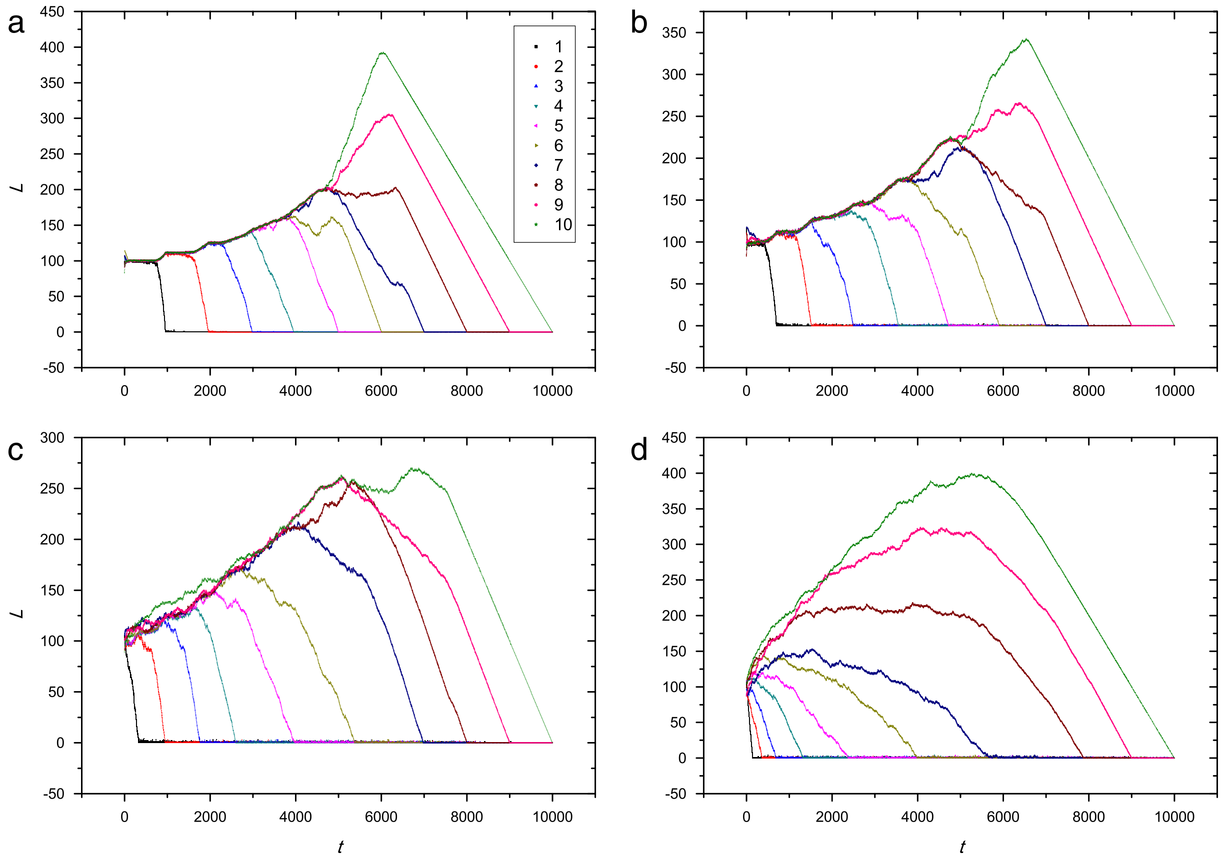

Fig. 4. (Color online) The change of the queue length L in each task with the time, and the parameters are the same with Fig. 1. (a), (b), (c), (d) respectively represent the corresponding results in the case of $p = 0, 0.3, 0.7$, and 1, respectively.

has a higher probability to first choose the less time-consuming task in the shortest queue strategy than in the random choice strategy. In other words, after a task was completed, an individual has a higher probability to first choose the time-consuming task in the random choice strategy than in the shortest queue strategy. This led to the result that the time spent for all tasks by an individual in the random choice strategy is less than that in the shortest queue strategy.

Fig. 4 shows the change of the queue length in a task with the time step for the case of $p = 0, 0.3, 0.7$, and 1. We define that L represents the queue length in each task. The $L(t)$ is varied with the time step t. When $p = 0$, we can find that the time step t_i spent for each task by all the individuals satisfies the function

$$t_i = 1000 \times \tau_i, \tag{3}$$

where i is the number of the task. The reason is that when $p = 0$, all the individuals choose the shortest queue strategy, therefore, unless all the individuals complete a task, the queue length L in the task is impossible zero, so t_i and τ_i satisfy the above functional relationship. When $p > 0$, because some individuals begin to choose the random choice strategy, the time step t_i no longer satisfies the functional (3). In the four sub-figures, it is obvious to find that the less the completion time of a task is, the faster the task is completed by all the individuals. Conversely, the more the time of completing a task is, the slower the task is completed by all the individuals. Whichever strategy each individual chooses, the time spent for all the tasks by all the individuals are 10,000 time steps, and this result is caused by the rules of our model. The time steps 10,000 are also the most time spent for all the tasks by an individual.

3. Conclusions

In this paper, we propose a model of MPM. Simulations and theoretical analysis have been done for this model and some interesting results have been found. First, the time spent for all tasks by an individual is calculated and the statistical law of the average time in each strategy is achieved. We find that the average time for the random choice strategy is much shorter than the one for the shortest queue strategy. This finding is very interesting, because people normally think that the shortest queue strategy can make them to spend less time in completing all the tasks in daily life. Therefore, if an individual changed the strategy from the shortest queue strategy to the random choice strategy, he may well spend less time in completing all the tasks and the average time of all the individuals could also be shortened. Second, the correlation coefficient between the order of each task processed by an individual and the corresponding time spent for all tasks by the individual are calculated. We find that if an individual first processed the time-consuming task and finally processed the less time-consuming task, he probably could spend less time in completing all tasks. The internal statistics law between the order and the corresponding time explains why the random choice strategy is better than the shortest queue strategy. Finally, we discussed the change of the queue length in each task with the time. These results have certain significance on researching the time optimization of MPM problems in the real world.

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