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Constructing a Relationship Model between Physical Training and Vocational Ability Enhancement of College Students in Public Security Colleges and Universities Using Support Vector Machine Algorithm

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Abstract Physical fitness quality, as the core quality of college students in public security colleges and universities, and its correlation with college students' vocational ability has gradually become a research hotspot in related fields in recent years. This paper identifies and judges college students' physical training actions by designing classifiers. At the same time, the gray correlation analysis method is used to analyze and construct the relationship model between physical fitness training and vocational ability of college students in public security colleges. By reflecting the relationship between physical training and occupational ability, it provides effective data reference and target guidance for the optimization and improvement of physical training programs. The design of the classifier is based on the identification process of physical training movements of college students in public security colleges, and adopts the Support Vector Machine algorithm (SVM) as the classification method of physical training movements and behaviors. Finally, the ant colony algorithm is introduced to optimize the kernel function of SVM algorithm to improve the classification accuracy and establish the physical training action classifier based on SVM. In the analysis experiment with a total of 154 college students from a public security university, the occupational ability performance scores of the students in the low level group improved up to 8.44 points compared with the pre-training scores after targeted physical fitness training.

Index Terms physical fitness training, occupational ability, support vector machine algorithm, gray correlation analysis method

I. Introduction

As the cradle of Chinese people's police training, public security colleges and universities play a crucial role in the development of police ability and quality [1], [2]. Since most of the work that Chinese police officers have to face in their daily work is characterized by high intensity, high activity intensity, long working hours, and the need for immediate explosive power, their bodies are required to have an efficient aerobic energy supply system [3]-[5]. Only when the body functions are kept in good condition can they both cope with the busy daily police work and strike quickly when encountering emergencies [6], [7]. However, at present, most public security colleges and universities are generally deficient in the physical training of college students, which not only affects their future professional ability, but also poses a threat to the overall quality of the police force [8]-[10].

With the development of society and changes in the law and order situation, the working environment and work tasks faced by the police are also changing, which puts forward higher requirements for the physical fitness of the police [11], [12]. As an important platform for cultivating future police talents, public security colleges should emphasize the cultivation of college students' sports ability [13]. In actual teaching, many public security colleges and universities pay little attention to physical training and one-sidedness of physical education, resulting in weaker physical education ability of college students, which is difficult to adapt to the increasingly complex requirements of police work [14]-[16]. By strengthening physical training and introducing diversified physical education teaching methods, the physical education ability of college students can be effectively enhanced, and a good foundation can be laid for their future police work by improving their vocational ability [17]-[19].

After identifying the 154 research subjects, the research idea on physical training movement recognition is briefly outlined. Under this framework, the support vector machine algorithm is used to classify the physical training behaviors of college students and construct a physical training movement classifier. Next, the gray correlation analysis method is introduced, and its application process and calculation steps are discussed in detail as the correlation analysis method between physical training and career advancement of college students in public security colleges. Subsequently, the career planning ability of the research subjects was analyzed to test the performance of the designed physical training action classifier. Finally, suitable research samples were selected to analyze the relationship between physical training intensity and career enhancement of college students in public security colleges based on the gray correlation analysis method, and the construction of the relationship model was completed.

II. SVM-based analysis of physical training

II. A. Selection of research subjects

One hundred students enrolled in their fourth year of college at a public security university in 2020 and 54 outstanding graduates who graduated in June 2020 were randomly selected, for a total of 154 public security college students as the study subjects.

II. B. SVM-based classifiers for physical training movements

II. B. 1) Algorithm Flow Overview

The flow of the algorithm for recognizing the physical training behaviors and actions of college students in public security colleges based on human skeletal keypoints is shown in Fig. 1.The method firstly carries out the detection of human skeletal keypoints, and then the extracted information about the location of the keypoints is processed by completing and so on. Then feature extraction is performed, and finally the extracted features are classified.

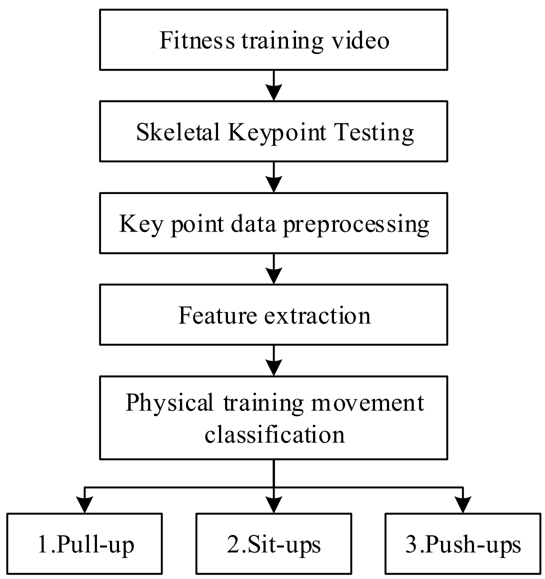

Figure 1: Algorithm flow

II. B. 2) Design of physical training movement classifier

Since there is no dataset for physical training action recognition, the dataset collected on the Internet and the dataset taken by ourselves are used, the dataset samples are relatively small, and there are only three types of actions, considering that the method of using deep neural networks will have overfitting linearity, and after comprehensive consideration, it is decided to use the Support Vector Machines (SVMs).SVMsSupport Vector Machines (SVMs) have a good ability in generalization, and they are suitable for processing small sample data and high dimensional data. Support Vector Machine is a supervised learning method that can be widely applied to classification as well as regression analysis. The core idea is to map vectors into a higher dimensional space where a maximum spacing hyperplane is established, and the sample points in the samples that play a decisive role are called support vectors. The addition of relaxation scalars improves the generalization ability of support vector machines, and the introduction of kernel functions enables SVMs to easily handle high-dimensional data. Essentially, SVM is a two-class classifier that cannot be used in multiclassification tasks, so it is necessary to construct a multiclassification SVM.There are two main types of methods for constructing a multiclass classifier for SVM: one is the direct method, which is a direct modification of the objective function that combines parameter solving for multiple classification surfaces into a single optimization problem, and “one-time” by solving that optimization problem. “The optimization problem is solved to realize multi-class classification. Another category is the indirect method, which mainly realizes the construction of multi-classifier by combining multiple binary classifiers, and the common methods are one-against-one and one-against-all. In this paper, the decision tree support vector machine constructed by one-against-all method is used, and the kernel width parameter σ and penalty parameter C of the support vector machine are optimized by using the ant colony algorithm, and then the feature vectors extracted from the physical training behaviors based on the key points of the human skeleton are taken as inputs, and then the physical training behaviors are classified in video after the decision tree support vector machine.

Ant Colony Algorithm (ACO) is a new type of simulated evolutionary algorithm, which was firstly proposed by Italian scholars.ACO belongs to a kind of swarm intelligent algorithms, which has the advantages of good robustness, good positive feedback characteristics and parallel search. ACO is used to search for the best objective function values and finally get the correct combination of parameter values. In our model, RBF is chosen, which is the most commonly used kernel function for SVM. So there are two parameters σ, C. What is to be done is to improve the classification accuracy by optimizing σ, C using ACO. The specific steps of the algorithm are described as follows:

(1) The initial parameter (σ, C) provided to each ant first.

(2) Based on the initial parameters (σ, C), after learning the training set by SVM, the error model of SVM is calculated as shown in Equation (1). Where Y_t is the value of the training sample and Y_r is the value of the real sample.

$$E(i) = \left| Y_t - Y_r \right| \tag{1}$$

(3) When the ant is at position i, its pheromone is represented as in equation (2). According to the formula, the smaller the error, the larger the pheromone, set $\alpha = 3$.

$$J_0(i) = \alpha^{E(i)} \tag{2}$$

(4) Based on the pheromone value of each ant, the transfer probability of each ant is obtained as in Equation (3). Where Bindex is the ant with the largest pheromone.

$$P_i = \frac{e^{J_0(Bindex) \cdot J_0(i)}}{e^{J_0(Bindex)}} \tag{3}$$

(5) In order to prevent getting a local optimal solution, this paper adopts an adaptive method. The volatilization coefficient of pheromone is set to be relatively small at the beginning, and increases continuously with the increase of the number of ants evolved, the volatilization coefficient of pheromone, as in Eq. (4). Where, here $K = 0.1$ and N is the existing number of ants in the evolved generation. $N_{\max}$ is the maximum number of ants in the evolutionary generation.

$$\rho = K \cdot \frac{\log(9) \cdot N}{e^{N_{\max}}} \tag{4}$$

(6) Pheromone update representation of SVM parameters based on ACO optimization as shown in Eq. (5).

$$J_0(i) = (1-\rho) \cdot J_0(i) + \alpha^{-E(i)} \tag{5}$$

At the end of an iterative work, the maximum pheromone is saved and the error is calculated according to the error model while the step goes to step (1) to continue. When the iteration meets the set frequency, the optimal ant is found to obtain the optimal parameters C and σ.

II. C.Gray correlation analysis

Gray correlation refers to the geometric correlation between two factors, using quantitative correlation to reflect the correlation between the two, and its value is expressed by 0~1, and the larger its value indicates the higher degree of correlation. Using the characteristics of the evaluation object, the gray correlation analysis is improved as a model, and the gray correlation analysis model based on the typical whitening weight function is constructed. The following are some basic definitions as well as calculation steps:

(1) Based on the research objectives, establish the analysis index system and collect the required data

Let the matrix of equation (6) be composed of n data series:

$$\left(X_1', X_2', \cdots, X_n'\right) = \begin{pmatrix} X_1'(1) & X_2'(1) & \cdots & X_n'(1) \\ X_1'(2) & X_2'(2) & \cdots & X_n'(2) \\ \vdots & \vdots & \ddots & \vdots \\ X_1'(m) & X_2'(m) & \cdots & X_n'(m) \end{pmatrix} \tag{6}$$

where m is the number of indicators, $X_i' = \left(X_i'(1), X_i'(2), \cdots X_i'(m)\right)^T$, $i = 1, 2, \cdots, n$.

(2) Selection of reference data columns

The reference data columns are prepared for the subsequent comparison of the correlations and are noted as equation (7):

$$X_0' = \left(X_0'(1), X_0'(2), \cdots X_0'(m)\right)^T \tag{7}$$

The composition of the reference data column can be the best value (or the worst value) of all indicators, or other reference data columns can be selected depending on the purpose of the evaluation. The closer the two data columns are, the greater the degree of association.

(3) Dimensionless processing of indicator data

Dimensionless data processing is because since each influencing factor in the evaluation object represents a different thing, the data that can be collected are also different, there is no way to compare or other problems occur in the comparison process, making it difficult to get the correct conclusion.

The transformation of the mean value method (8), the initialization method (9), and the transformation of equation (10) are the basic methods of dimensionless processing.

$$x_i(k) = \frac{x_i'(k)}{\frac{1}{m}\sum_{k=1}^{m} x_i'(k)} \tag{8}$$

$$x_i(k) = \frac{x_i'(k)}{x_i'(1)} \tag{9}$$

$$\frac{x - \bar{x}}{s} \tag{10}$$

where $i = 1, 2, \cdots, n$; $k = 1, 2, \cdots, m$.

The matrix of Eq. (11) is composed of a sequence of dimensionless data:

$$\left(X_0, X_1, \cdots, X_n\right) = \begin{pmatrix} X_0(1) & X_1(1) & \cdots & X_n(1) \\ X_0(2) & X_1(2) & \cdots & X_n(2) \\ \vdots & \vdots & \ddots & \vdots \\ X_0(m) & X_1(m) & \cdots & X_n(m) \end{pmatrix} \tag{11}$$

(4) The indicator sequence, that is, the absolute value of the difference between the comparison sequence and the corresponding element of the reference sequence, is calculated separately for each evaluated object, i.e., $\left|x_0(k) - x_i(k)\right|$, where $i = 1, 2, \cdots, n$; $k = 1, 2, \cdots, m$. The number of evaluated objects is n.

(5) Determine the minimum second order difference $\min_{i=1}^{n} \min_{k=1}^{m} \left|x_0(k) - x_i(k)\right|$ with maximum second degree difference $\max_{i=1}^{n} \max_{k=1}^{m} \left|x_0(k) - x_i(k)\right|$.

(6) Calculate the association coefficient

Gray correlation coefficient refers to the important coefficient that can reflect the correlation between the reference sequence and the comparison sequence, which is obtained from the absolute difference of these two data series. According to equation (12), the correlation coefficient between each comparison sequence and the corresponding element of the reference sequence can be calculated.

$$\zeta_i(k)=\frac{\min_i\min_k\left|x_0(k)-x_i(k)\right|+\rho\cdot\max_i\max_k\left|x_0(k)-x_i(k)\right|}{\left|x_0(k)-x_i(k)\right|+\rho\cdot\max_i\max_k\left|x_0(k)-x_i(k)\right|} \tag{12}$$

where $\zeta_i(k)$ is the correlation coefficient of the k evaluation factor of the i evaluation unit, $k=1,2,\cdots,m$, and $\rho\in(0,1)$ denotes the discrimination coefficient. The strength of the discriminating ability is determined by the value of ρ, usually ρ is taken as 0.5 to ensure $\zeta_i(k)\in(0,1]$.

When the reference series uses the optimal (or worst) value of each indicator, an improved and simpler method such as equation (13) can also be used:

$$\zeta_i(k)=\frac{\min_i\left|x_0(k)-x_i'(k)\right|+\rho\cdot\max_i\left|x_0(k)-x_i'(k)\right|}{\left|x_0'(k)-x_i'(k)\right|+\rho\cdot\max_i\left|x_0(k)-x_i'(k)\right|} \tag{13}$$

Because of some adverse effects that the dimensionless treatment will bring to the indicator, the improved formula not only makes the calculation easier, but at the same time eliminates the adverse effects.

(7) Determination of correlation order

The correlation order can reflect the correlation between each evaluation object and the reference series, which is calculated by the correlation coefficient corresponding to the comparison series and the reference series, and then take the average value of the correlation coefficient, which is expressed as formula (14):

$$r_{oi}=\frac{1}{m}\sum_{k=1}^{m}\zeta_i(k) \tag{14}$$

where $r_{oi}=\left(1,2,\cdots,m\right)$ is the gray correlation of the m th evaluation factor.

(8) Differences in the role played by the indicators can be eliminated by finding the weighted average of the correlation coefficients, expressed as equation (15):

$$r_{oi}'=\frac{1}{m}\sum_{k=1}^{m}W_k\cdot\zeta_i(k) \tag{15}$$

where W_k is the weight of each index, $k=1,2,\cdots,m$.

(9) According to the correlation order of each evaluation object, the evaluation results are analyzed.

III. A model of the relationship between physical training and career advancement

This chapter further explores the recognition performance and settings of the proposed SVM-based physical training classifier, and with the technical support of this classifier, the relationship analysis between physical training and vocational ability enhancement of college students in public security colleges and universities is carried out by using the gray correlation analysis method, so as to construct a relationship model between physical training and vocational ability enhancement of college students in public security colleges and universities.

III. A. Current status of the level of competence in career planning

Career planning questionnaires were distributed to 154 research subjects, 154 questionnaires were distributed, 150 valid questionnaires were returned, and the validity rate of the questionnaires was 97.40%. The questionnaire was divided into 6 major parts: (A) self-knowledge, (B) environmental knowledge, (C) establishing goals, (D) making plans, (E) adjusting and optimizing, and (F) career planning. In this questionnaire, the Richter five-point assessment method is adopted to evaluate the level of an individual's career planning ability. "1" represents "completely inconsistent", "2" represents "not quite consistent", "3" represents "in between", "4" represents "somewhat consistent", and "5" represents "completely consistent". The level of career planning ability is distinguished by the following five rating grades: [1,1.80] indicates very weak ability, [1.81,2.60] indicates relatively weak ability, [2.61,3.40] indicates average ability, [3.41,4.20] indicates good ability, and [4.21,5.0] indicates excellent ability. The current status of career planning ability and level of 150 college students from public security colleges is shown in Table 1.

Table 1: The current situation of college students' career planning ability and level

	Number	Mean value	Standard deviation
(A)	150	3.582	0.7891
(B)	150	3.0186	0.9465
(C)	150	3.5318	0.8146
(D)	150	3.4153	0.7404
(E)	150	3.8738	0.7669
(F)	150	3.4843	0.6889

(F) The overall mean score of career planning is 3.4843, which is in the range of 3.41-4.20 interval, indicating that the overall level of career planning competence of 150 university students is good. According to the mean values of the different components of career planning competence, in descending order, they are (E) adjustment and optimization, (A) self-awareness, (C) establishing goals, (D) making plans and (B) environmental awareness. The lowest mean value is (B) environmental awareness, which is only 3.0186, indicating that college students do not have sufficient knowledge about the employment environment.

III. B. Performance analysis of physical training movement classifiers

Five kinds of videos with resolution standards of 480p, 720p, 1080p, 2k and 4k are selected as test inputs for the performance analysis of the classifier designed in this paper and the classifier based on deep neural network algorithm, and the experimental platform has a GPU of GTX1650ti with 4G of video memory, and a CPU of AMDRyzen7 4800H. The results of the two classifiers on the classification of college students' physical movements are shown in Fig. 2. The running results of the two classifiers for the classification of college students' physical movements are shown in Fig. 2. The detection speed of the classifiers in this paper is better than that of the classifier based on the deep neural network algorithm. When the input resolution is less than 2k, the running speed of this classifier basically meets the demand of real-time detection, while the running speed of the deep neural network-based classifiers are all below 20FPS. And the classifier in this paper can completely rely on CPU computation, requiring less computational resources. In terms of the physical action posture extraction effect, since the deep neural network-based classifier presets that all the people appearing in the screen are in an upright state, the accuracy will be greatly affected when there is a prone action in the screen.

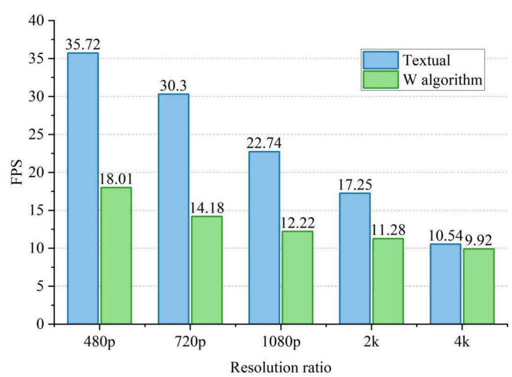

Figure 2: The running result of the classifier for action classification

The classification running speed of this paper's classifier for multiple college students' physical training behavioral actions is shown in Fig. 3. A total of four college students were selected: BA1, BA2, BA3, and BA4, which corresponded to bottom-up (2 people), top-down (2 people), bottom-up (4 people), and top-down (4 people), respectively.

The top-down approach requires running additional classifiers to extract the outer human body edges of all college students in the image, and then performs single-person physical action recognition separately, which slows down the algorithm as the number of people to be tested increases and the number of times the physical action classifiers need to be run increases. The bottom-up approach runs better than the top-down approach because it does not need to run additional classifiers, and its running speed is negatively correlated with the input size of the test and is not affected by changes in the number of people to be detected. The bottom-up method runs faster, but the maximum detection speed does not reach 20 FPS. To meet the demand for real-time detection, frame interval detection can be performed according to the input video frame rate to match the detection speed with the input video frame rate.

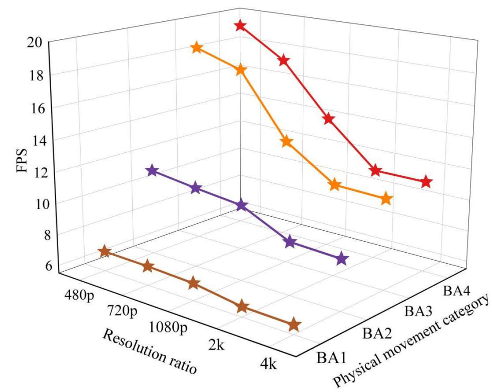

Figure 3: The classification speed of physical movements for multiple people

III. C. Analysis of the relationship between physical training and vocational ability enhancement

III. C. 1) Basic information on the subject of the study

Based on different physical fitness qualities, they were divided into the following three groups: (G1) high level, (G2) medium level, (G3) low level as shown in Table 2, and the physical fitness information of 154 college students as shown in Table 2.For the convenience of calculation, the different levels of physical fitness qualities were assigned with scores, in which full scores were 10 points, and the scoring intervals of the (G1) high level group was [8,10], the scoring intervals of the (G2) medium level group was [5,7], and the scoring intervals of the (G3) high level group was assigned a score interval of [0,4].

Table 2: The basic information of the research object

Group	Sample size	Age	Height (cm)	Weight (kg)
G1	34	22.76±0.95	178.75±2.05	69.08±2.94
G2	78	23.93±2.52	175.60±5.04	70.02±6.72
G3	42	22.67±3.71	172.66±5.38	72.79±9.25

III. C. 2) Analysis of the association between physical training programs and occupational competence

Based on the analysis above, this paper adopts the form of numerical value to represent the occupational ability of college students in public security colleges. The occupational ability is categorized into five grades: (C1) excellent, (C2) good, (C3) average, (C4) qualified, and (C5) unqualified, which correspond to the score intervals of [90,100], [80,89], [70,79], [60,69], and [0,59] in that order. The occupational ability performance of students in different physical fitness groups is shown in Fig. 4. In terms of occupational ability performance, students in the (G1) high-level group had the highest overall mean value of 86.11, which belonged to the (C1) excellent range and the overall distribution was relatively compact, indicating that the overall strength of students in the (G1) high-level group was relatively strong, and there was no obvious gap within the group. (G2) The middle level group of college students' vocational ability performance is the next best, with an overall mean of 77.86, which belongs to the (C3) general range. (G3) College students in the low level group have less satisfactory performance in vocational ability, with an overall mean of 68.92, which belongs to the (C4) qualified range.

It can be seen that the physical fitness performance of students in public security colleges and universities shows a consistent trend of change with their occupational ability performance. Accordingly, this paper initially puts forward the research conjecture that the physical fitness performance of students in public security colleges is positively correlated with their occupational ability performance. Based on this, the designed SVM-based physical training movement classifier is used to identify the physical training movements of different groups of students, and different training optimization schemes are given. After training, gray correlation analysis was used to focus on the physical fitness and occupational performance ability of students in the original (G2) medium level group and (G3) low level group see Figure 5.

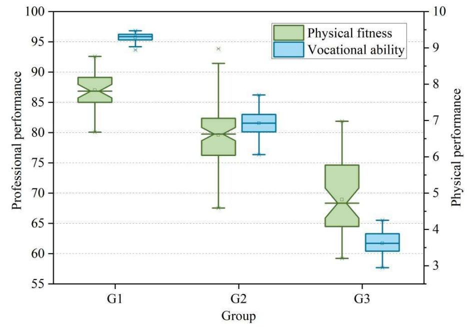

Figure 4: The professional ability performance of students in the three groups

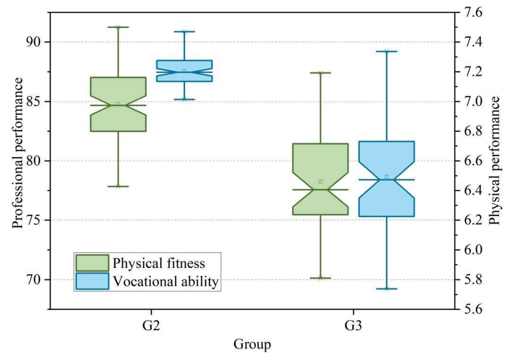

Figure 5: Physical performance and overall professional ability after training

After the training based on the classifier training program, the level of physical fitness quality of students in (G2) middle level group and (G3) low level group were improved to some extent. And compared with the pre-training of optimization, the mean score of occupational performance of (G3) intermediate level group increased by 6.9 points to (C2) good range. The mean score of occupational performance of (G3) low level group has increased by 8.44 points, which is a significant improvement and reaches (C2) good range. It can be found that with the improvement of the level of physical fitness quality, the occupational performance of students in public security colleges and universities also has a significant improvement, which verifies the research conjecture of this paper.

IV. Conclusion

In this paper, a physical training action classifier based on SVM is designed, which is used to identify and judge the physical training actions and behaviors of college students in a public security academy, and give the training optimization plan. At the same time, the gray correlation analysis method was chosen as a method to analyze the relationship between physical training and vocational ability enhancement of college students in public security colleges. Compared with similar classifiers, the designed classifier can completely rely on CPU computation, which requires less computational resources. In the experiment of analyzing the relationship between physical training and vocational ability enhancement, the training program using the classifier recognition results as a reference can effectively assist in the enhancement of the physical fitness quality level of the students in the low level group, and thus lead to the enhancement of the vocational ability of the students in this group. Compared with the pre-training period, the occupational ability of the students in the low level group improved up to 8.44 points.

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