Research on the Recommendation of Exercise Recovery Duration of Mobile Health APP

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Abstract. With the further deepening of people's demand for health, the use of mobile health apps has become more popular. The recovery duration suggestion function of the mobile health App can provide more scientific exercise guidance and good exercise experience, but there are still some shortcomings, such as low data utilization, and the suggestion is difficult to be accurate to individuals. In this paper, questionnaire survey is used to collect data, and a hidden Markov prediction model based on K-means clustering analysis is established. Through training the collected data, a more scientific analysis of the recovery time after exercise can be finally given. Finally, we give some suggestions on the future development of sports bracelets.

Keywords: Exercise heart rate recovery, K-means clustering, Hidden Markov model, Mobile Health APP.

1. Introduction

People's health is an important manifestation of national prosperity and national prosperity. As China continues to move towards developed countries, people and the country's pursuit of health is also rising. Relevant data show that the scale of China's massive health industry will reach more than 10 trillion yuan in 2023, which is a trillion level blue ocean market with huge development space. At the level of national policy guidance, healthy China has been promoted to the strategic level.

In view of the fast pace of modern life, people often report that it is difficult to obtain health promotion plans, including suggestions, information, feedback and self-monitoring; Therefore, mobile applications can provide relevant solutions and suggestions for healthy life and sports. The rapid development of the mobile phone industry provides a new way to promote health [1]: the rapid development of emerging technologies encourages the use of smart phones in sports research, and makes personalized data analysis and future operation suggestions on the recovery time of human movement through smart platforms, one-stop software, etc.

Nowadays, the use of smart mobile health technology has become the focus of human health index measurement and chronic disease management and prevention. Previous research has explored the usability of mobile applications in changing smoking behavior, managing diabetes and enhancing the effect of weight loss [2-3]. Mobile health software has gradually shown the potential of letting individuals participate in the management of their own physical functions. Smart phone subscriptions are ubiquitous around the world, and mobile health applications are used to bring hope to health practitioners and health behavior intervention research [4].

At this stage, although the healthy application of mobile devices and wearables in business and research continues to experience tremendous growth, due to the lack of theory and short technology investment time, and the use of smart phones is still a relatively new research field in sports research, the existing positive impact of their assistance in sports and health care has not been fully captured, little is known about its effectiveness as a measurement and intervention tool [5]. Although many applications related to physical activity are available on the main smartphone platforms, there are relatively few relevant studies on testing to determine their effectiveness in promoting health.

Based on the low utilization rate of exercise data in the existing software and the lack of personalized suggestions from customers, this project collects the heart rate data of subjects of different ages through questionnaires on the basis of the existing APP, fits the heart rate change image through K-means clustering analysis, and classifies it, and calculates the recovery time after exercise differently according to different populations and special conditions, So as to establish a personalized exercise recovery duration model to supplement the deficiencies in the existing mobile health apps.

2. Conceptual design

With the help of the heartbeat data before and after exercise in the user's field experiment, the project collects the user's personal baseline information and exercise fatigue status through the questionnaire method, mainly uses K-means clustering analysis and hidden Markov model, divides the user's exercise ability through K-means clustering analysis, gives the definition of the heart rate recovery state standard, and uses hidden Markov model to find the recommended benchmark of reasonable exercise recovery time, So as to recommend a humanized recovery time. Finally, this project will use the change image of heartbeat data to classify, so as to establish a personalized rest duration recommendation model.

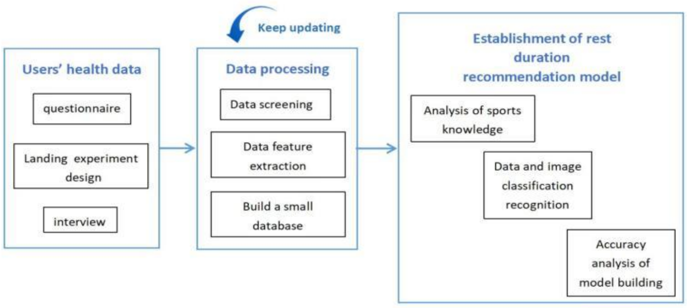

Figure 1. Schematic Design Flow Chart

According to the research questions, we first designed a basic questionnaire to conduct a pre survey. We selected three static characteristics: smoking, staying up late, and drinking.

3. Main contents of the study

3.1. Heart rate data grouping based on K-means clustering analysis

K-means clustering algorithm has excellent convergence speed and scalability when processing big data. The essence of this algorithm is to judge the similarity between different points by calculating their location distance, and put the points with high similarity in the same class or cluster.

The algorithm first selects K cluster centers, classifies the samples to the nearest center according to Euler's formula, calculates the mean value of the same class of points, and takes this mean value as the new cluster center. Repeat the above process to update the cluster center until the cluster center no longer changes.

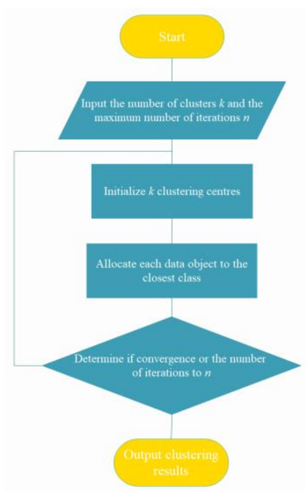

Figure 2. Flow chart of K-means clustering analysis algorithm

3.1.1 Data preprocessing

The heart rate before exercise is the normal heart rate in human life. The heart rate of ordinary people is generally 60-100 beats/minute, which can meet this figure, indicating that the heart rate is relatively normal and the physical fitness is relatively good. This heart rate may be higher than the normal heart rate before exercise.

The heart rate when getting up the next day is the morning pulse. The morning pulse can reflect the heart rate needed to maintain the most basic metabolism of life activities when the human body is awake, without excessive exercise consumption and interference of neural factors. It reflects the working ability and state of the heart when maintaining the most basic metabolism of the human body.

The average heart rate in exercise can reflect the intensity of exercise, and can also control the running speed and exercise intensity of athletes through the determination of heart rate.

The average heart rate of exercise, the heart rate before going to bed on the same day and the heart rate after getting up the next day will be affected to some extent by exercise, resulting in a certain deviation from the heart rate before exercise (i.e. normal heart rate). Therefore, we make a difference to them, and use three groups of heart rate difference data to evaluate the recovery state of the body. The calculation formula is as follows: (1) Heart rate difference during exercise = average heart rate during exercise - heart rate before exercise. (2) Heart rate difference before sleep = heart rate before sleep that day - heart rate before exercise. (3) Heart rate difference when getting up the next day = heart rate when getting up the next day - heart rate before exercise.

3.1.2 Selection of K

There are n=100 groups of data in the total data set, so we adopt the root mean square method:

$$K = \sqrt{\frac{n}{2}} \tag{1}$$

After rounding down K, we get K_0=7.

But after K-means clustering analysis, we found that there were three groups of problematic data in 100 groups of data, it is unrepresentative and has no specific meaning if it is divided into one category separately. Therefore, we combined three groups of noisy data with problems, and finally K=5 was presented in our study.

3.1.3 K-means algorithm processing results

The processing result is shown in Figure 3, where the vertical axis represents the distance between various categories (the distance has been rescaled and standardized), and the horizontal axis represents data. It can also be seen from the figure that we can cluster into 5-7 categories. The specific classification is shown in the following chart:

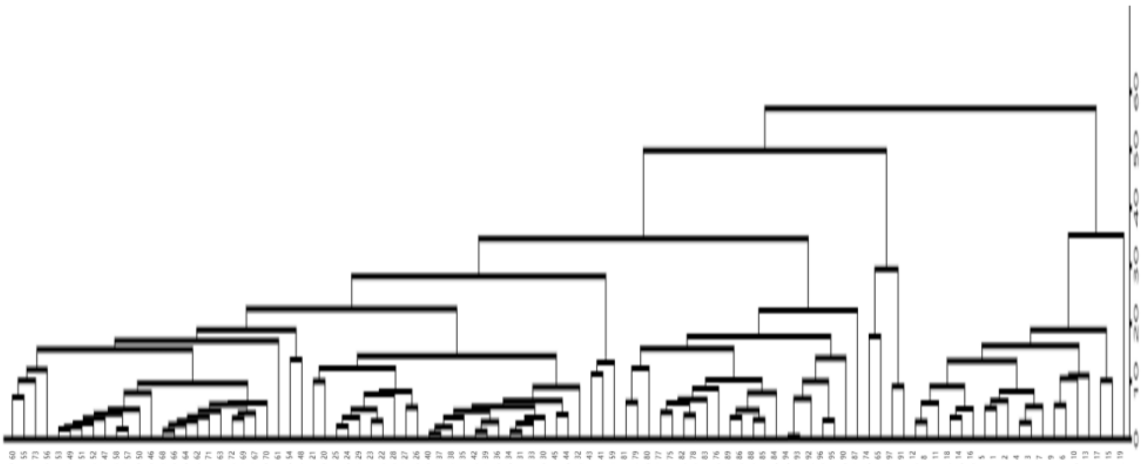

Figure 3. Cluster pedigree of processing results

Table 1. K-means cluster analysis results

Type	Data
1	32, 38, 40, 41, 42, 53, 55, 56, 57, 58, 59, 73, 74, 91, 92, 93, 94, 95
2	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 33, 34, 35, 36, 37, 48, 49, 50, 52, 60, 61, 62, 63, 64, 65, 72, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 100
3	43, 44, 45, 46, 66, 99
4	39, 51, 71
5	17, 54, 67, 47, 68, 69, 70, 96, 97, 98

3.1.4 Analysis of K-means algorithm results

Type 1 testers need a certain amount of time to recover after exercise. It is not recommended that they take new exercise after a certain intensity of exercise on the first day, but they can basically continue to exercise when they get up in the morning the next day.

Type 2 testers have good physical fitness and strong sports recovery ability. After sports, they can continue to exercise that night by supplementing appropriate water.

Type 3 testers should perform mild exercise based on the exercise duration and heart rate change, so they do not need a long recovery time.

Data of type 4 testers, which we think is problem data.

Type 5 testers may have weak physical fitness. According to their heart rate, we believe that such users cannot exercise when they get up the next day and need further rest in particular, the 98th tester, after a long time of high-intensity exercise, had better not exercise with a certain intensity the next day.

3.2. Prediction of heart rate recovery duration based on hidden Markov model

Hidden Markov Model (HMM) is a statistical model. Each state represents an observable event, which limits the adaptability of the model to some extent. This paper studies the problem of the duration of heart rate recovery after exercise. For people, it may not be possible to directly obtain whether the body is fully recovered to the next exercise. Therefore, we hope to judge the state of body recovery by the change of heart rate. Therefore, the degree of body recovery is a hidden state, and the change of heart rate is an observable state. We hope to use the Hidden Markov Model to predict the recommended recovery time through the change of heart rate and Markov hypothesis when the body recovery state cannot be directly obtained.

3.2.1 Application of K-means cluster analysis conclusion

Before using Hidden Markov Model, we use K-means clustering analysis to define the heart rate standard of recovery state.

In the K-means cluster analysis in 4.1 of this article, our K selected a value of 5. Since we pay more attention to the state of heart rate recovery here, we remove the data of the abnormal value group, and divide the state of heart rate recovery into three groups: "you can exercise that night", "you can exercise the next morning", and "you cannot exercise the next morning, and you need to rest further". Select K=3 again for cluster analysis.

According to the conclusion of cluster analysis, as the benchmark of learning, the three states are: "I can exercise that night", "I can exercise the next morning", and "I can't exercise the next morning and need further rest". The three classifications of exercise time are below 0.9h, 0.9h - 1.6h and above 1.6h. The average heart rate difference during exercise is divided into three categories: below 60, 60-81 and above 81. Current classification of heart rate difference before sleep: below -0.5, -0.5 -3.5, and above 3.5. Finally, 97 groups of data (excluding three groups of abnormal values) were divided into three categories: 68 were able to exercise that night, 18 were able to exercise the next morning, and 11 were unable to exercise the next morning, requiring further rest.

3.2.2 Specific steps of hidden Markov model algorithm

Generally, a hidden Markov model is recorded as: λ= [π, A, B], the following three elements need to be determined:

(1) Initial state probability π: the probability of the occurrence of each state of the model at the initial time, usually recorded as $\pi = (\pi_1, \pi_2, ..., \pi_N)$, π_i represents the probability that the initial state of the model is S_i.

(2) State transition probability A: the probability of model transition between states, usually recorded as matrix A [a_{ij}], where a_{ij} represents the probability that at any time t, if the state is S_i, the state at the next time is S_j.

(3) Output observation probability B: the probability that the model obtains each observation value according to the current state is usually recorded as matrix B=[(b_{ij})]. Where, b_{ij} represents t at any time, if the state is S_i. Then the probability of observation value [O_j] being obtained.

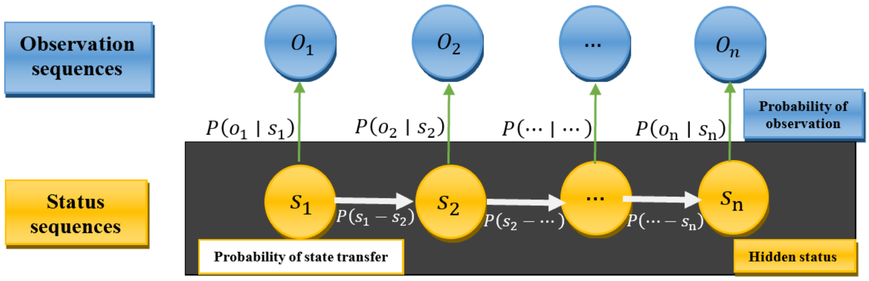

Figure 4. Hidden Markov Process

Given Hidden Markov Model λ= [A, B, π], which generates the obsrvation sequence {X_1, X_2, ... , X_n} according to the following process:

(1) Set t=1, and select initial state Y according to initial state probability π_1;

(2) Select observation variable X according to state value and output observation probability B_t;

(3) Transfer the model state according to the state value and state transfer matrix A, that is, determine Y_{t+1};

Based on the graph structure of Hidden Markov Model, the joint probability distribution of all variables is:

$$P(O_1, S_1, \cdots, O_n, S_n) = P(S_1) P(O_1 \mid S_1) \prod_{i=2}^{n} P(S_i \mid S_{i-1}) P(O_i \mid S_i) \tag{2}$$

Where, $S(S_1, S_2, \cdots, S_n)$ is the state variable and $O(O_1, O_2, \cdots, O_n)$ is the observation variable.

3.2.3 Implementation of Hidden Markov Model

First, HMM learning is required, that is, determining the corresponding parameters of HMM. λ Estimating parameters for the model, λ= [π, A, B], where π is the initial state probability, A is the state transition probability matrix, and B is the output observation probability matrix.

Determine model estimation parameters λ= For each element in [π, A, B], load the HMM toolbox into the MATLAB software, and write the. m file program. We have selected three states: "you can exercise that night", "you can exercise the next morning", and "you cannot exercise the next morning, and you need further rest". The probability distribution of heart rate was observed, and the HMM model of heart rate recovery data was obtained by training 97 groups of heart rate data after noise removal. The following results were obtained after training:

$$\pi = (0.7, 0.2, 0.1) \tag{3}$$

$$A = \begin{bmatrix} 0.15 & 0.3 & 0.55 \\ 0.53 & 0.32 & 0.15 \\ 0.23 & 0.47 & 0.3 \end{bmatrix} \tag{4}$$

$$B=\begin{bmatrix}0.5 & 0.5\\ 0.2 & 0.8\\ 0.2 & 0.8\end{bmatrix} \tag{5}$$

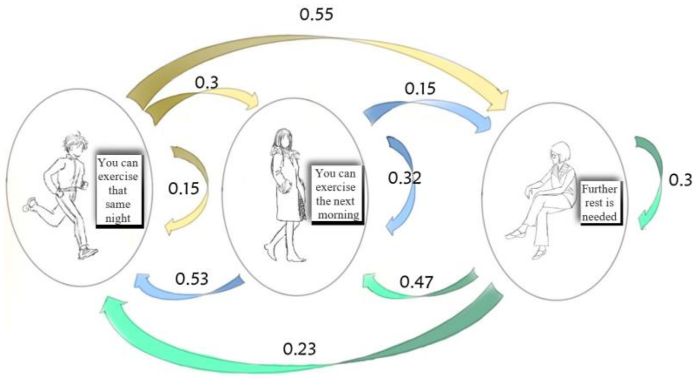

Figure 5. Schematic diagram of state transition probability matrix

The final model only needs to input a set of test set data of the user: average exercise heart rate, heart rate before going to bed that day and heart rate after getting up the next day. The state of the exercise heart rate data of this group of data is classified by K-cluster analysis, and then the analysis results of 100 sets of training set data are obtained by using hidden Markov model, that is, the state transition probability matrix shown in Figure 5. After this exercise, make a good estimate of the time you can exercise next time.

4. Prospect of bracelet

4.1. Sports APP

The constant technological development and the development of new mobile devices such as smart phones and tablets provide a higher level of comfort and practicality, thus making such devices the life center of current consumers with the development of information technology [6], sports apps have gradually penetrated into the appointed life. Because of its visual data, rich content and various choices, it has become a popular tool for fitness exercise. In addition to providing more scientific exercise methods for people to exercise, sports APP are also widely used in online and offline hybrid teaching [7]. The diet and fitness guidance provided is more popular [8], and the group targeting is gradually weakening, which is accepted by the majority of information users.

In the actual use of APP, the existing problems cannot be underestimated. Most sports APPs not only require users to have strong self-control, but also need to choose exercise intensity independently; As an intelligent software, it is inevitable that there will also be program vulnerabilities and errors, such as inaccurate AI rope skipping count. In addition, the overall effect of sports APP is general, but under certain conditions, APP can better promote physical exercise. This also shows that sports APP needs more rigorous and scientific comprehensive consideration to achieve better functionality [9].

4.2. Smart bracelet

The emergence of intelligent sports bracelet leads the trend of fitness. It monitors daily physical activity data and shares it with sports apps. Sports APP and sports bracelet are interrelated, perform their respective duties and complement each other, which has a positive role in guiding healthy life [10]. Motion monitoring is the most important function of the sports intelligent bracelet. It can accurately record the user's daily walking steps. Motion monitoring usually displays the exercise time, leisure time, exercise mileage, walking steps and energy consumption of the day [11]. This paper focuses on calculating heart rate with an intelligent bracelet and giving guidance on recovery after exercise. Nowadays, exercise bracelets generally have the function of heart rate measurement, and the heart rate is measured more accurately, but they lack the function of analyzing the heart rate value and giving recovery opinions. In future applications, we hope to add the function of analyzing different sports situations to the bracelet, and provide users with not only cold numbers, but also a more guiding recovery plan after sports.

4.3. Special conditions of different populations

This study collected a lot of data, classified everyone who provided the data, and conducted a study on "whether there are smoking, drinking, staying up late and special conditions". We hope that the future sports bracelets and sports apps can also provide specific sports recovery programs for different populations and situations through the analysis of exercise heart rate. For example, men and women (different genders), regular sports people and sedentary people (different sports habits), different categories of people will inevitably have different recovery cycles after sports; Another example is whether to stay up late, whether to drink, and even whether women have menstruation. These special circumstances will also cause a large fluctuation in the recovery cycle after exercise. We hope that the mobile health APP and sports bracelet will be equipped with relevant functions in the future. Through the analysis of the heart rate value during exercise, and in combination with the user's basic physical conditions and recent special circumstances, we can provide a guiding recovery time through algorithms, and even provide a recovery plan.

5. Conclusion

The innovation points of this paper are mainly in three aspects. The feasibility is very strong and easy to operate, the personalized design is more practical, and the recovery time prediction is more accurate.

(1) The bracelet provides data monitoring. The K-means clustering analysis is used to preliminarily classify the data. The final recommended recovery duration can be given according to the classification of the sports population. We can synchronously display the results on the App, and provide more services through data analysis.

(2) When users use the bracelet for longer, they can train the HMM hidden Markov model based on K-means clustering analysis of users' past data to obtain a model of post exercise body recovery market that conforms to users' own physical conditions, which can more accurately and personalized predict the recovery time of exercise heart rate. In addition, we not only considered age and gender when collecting data, but also paid special attention to other physical conditions of users on that day, such as sleep quality and bad habits.

(3) We will combine the HMM hidden Markov prediction model trained from 100 groups of data we collected with K-means clustering to predict the recovery time, and use the two methods to analyze at the same time to make the recommended recovery time more reliable. Different from person to person, to ensure the rationality of the scheme provided to the greatest extent.

References

[1] Guo Chengzhi Research on the Design and Implementation of Sports Fitness Monitoring APP [D]. Guangzhou Institute of Physical Education, 2017.

[2] Abroms LC, Padmanabhan N, Thaweethai L, Phillips T. iPhone apps for smoking cessation: a content analysis. Am J Prev Med 2011 Mar; 40(3): 279-285.

[3] Pagoto S, Schneider K, Jojic M, DeBiasse M, Mann D. Evidence-based strategies in weight-loss mobile apps. Am J Prev Med 2013 Nov; 45(5): 576-582.

[4] Knight E, Stuckey M, et al. Public Health Guidelines for Physical Activity: Is There an App for That? A Review of Android and Apple App Stores [J]. 21.5.2015 in Vol 3, No 2(2015): Apr-Jun.

[5] Judit Bort-Roig 1, Nicholas D Gilson, et al. Measuring and influencing physical activity with smart phone technology: a system review [J]. Sports Med. 2014 May; 44(5): 671-86. doi: 10.1007/s40279-014-0142-5.

[6] Kim, Y., Kim, S., et al. The effects of consumer innovativeness on sport team applications acceptance and usage. J. Sport Manag. 2017, 31, 241–255.

[7] He Zhiyu Application of Sports APP in Student System Education [J]. Gansu Education. 20221004-0463 (2022) 12-0031-04.

[8] Angosto, S., Valantine, I., et al. The Intention to Use Fitness and Physical Activity Apps: A Systematic Review. Sustainability 2020, 12(16), 6641; https://doi.org/10.3390/su12166641.

[9] Lou Hu, Liu Ping. Can sports and fitness apps promote physical exercise —— Evidence from meta-analysis [J]. China Sports Science and Technology, 2022, 58(06): 94-103. DOI: 10. 16470/jcsst. two million twenty thousand and eight.

[10] Zhao Ruyi, Bao Wangyu. Research on the influence of intelligent sports bracelets on sports behavior and habits [J]. Sichuan Sports Science, 2021, 40(03): 62-66.

[11] Jiang Shishi, Zhang Yanqiu. Research on the mechanism of innovative sports products to promote national fitness -- taking the sports smart bracelet as an example [J]. Contemporary Sports Science and Technology, 2022, 12(04): 185-188. DOI: 10.16655/j.cnki.2095-2813.2109-1579-5350.