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CHANNEL ESTIMATION OF URBAN 5G COMMUNICATION SYSTEM BASED ON IMPROVED PARTICLE SWARM OPTIMIZATION ALGORITHM

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Abstract. In order to solve the problem that the channel estimation accuracy of the traditional urban communication system is not high, the author proposes the channel estimation of the urban 5G communication system based on the improved particle optimization algorithm. This method converts the channel estimate into a regression fit and adjusts the fit. Focusing on regression fitting problems, big data models are used to display offline data, study channel nonlinearities, and obtain initial channel prediction models. To solve the adaptive problem, the author collects real-time teaching data in a real online learning mode and integrates blended learning to update the model, to avoid the problem of overspending on offline training. Offline tests show that the performance of the channel estimation model is the best for different channels. As the signal-to-noise ratio increases, the MSE value is stable at around 1200. Conclusion: The channel estimation method can produce different characteristics of channel estimation in different situations and improve the signal recovery function of the communication system.

Key words: Channel estimation, Improved particle swarm optimization algorithm, Integrated learning

1. Introduction. With the popularization of smart terminals and the emergence of many new mobile applications, there will be high requirements for wireless transmission speed, minimum delay, and network access support for multiple terminals. It can be assumed that a 4G system will be available in the near future. Due to the difficulty of meeting the demand for mobile communication services, countries around the world have started researching 5th generation (5G) mobile communication. Those. By 2022, the capacity of commercial 5G systems should be 1,000 times greater than the current 4G systems.

In the context of the continuous expansion of the scale of mobile communication services, 5G has become a new generation of mobile communication technology. 5G networks will cost less, consume less energy, have larger communication capacity, and be more secure and reliable. Compared with 3G and 4G, 5G's transmission rate can reach the millisecond level, and the device connection density is 10 to 100 times higher than that of 4G. In addition, 5G network can overcome the space-time limitation of information communication, greatly shorten the distance between people and things, and realize high-speed interconnection between people and things, for example, iot applications such as smart grids, smart healthcare, and driverless cars are expected to become a reality. Compared to 5G, 3G and 4G are more focused on mobile broadband applications, while 5G networks are more focused on the speed of wireless connections. The advantages of 5G are not only reflected in individual users, but also in public safety, for example, remote monitoring of emergency call drones and tracking of emergency personnel rely on the high speed, high density connection and high reliability of 5G networks. The continuous increase in demand for new 5G technologies and the emergence of new communication scenarios have promoted the emergence of technologies with development potential in 5G communication systems.

In particular, the proposal of massive MIMO technology has become a hot topic in the industry. Massive MIMO technology is suitable for multi-user scenarios on the side of 5G base stations. If the number of antennas at the base station side goes to infinity, the user channel vectors gradually tend to be orthogonal. Theoretically, this eliminates user interference in the same cell. The increase in the number of antennas also brings a series of problems and challenges, such as pilot pollution. At present, the theories related to massive MIMO technology have been relatively mature, but more comprehensive and in-depth research is needed to give full play to the role of the technology, and channel estimation and equalization technology is one of the key research directions.

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Multiple-input-multiple-output (MIMO) technology can simultaneously reuse multiple data streams on the spectrum by installing multiple antennas at the transmit and receive sites to improve system spectrum utilization. By installing more antennas at the base station, more data streams can be used simultaneously back on the spectrum device, which means that more terminal users can work at the same time. In order to support multiple UTs simultaneously with massive MIMO systems, MIMO systems with multiple antennas installed at the base station are being advocated in academic and commercial circles. And they do a lot of research on MIMO systems.

At present, channel estimation methods for massive MIMO mainly include blind channel estimation, semi-blind channel estimation, channel estimation, and compressed sensor-based estimation. Among them, the test based on channel estimation is less computationally intensive and easy to implement, such as LS channel estimation and MMSE channel estimation.However, this kind of channel estimation algorithm needs to be supplemented with pilot signal, which is easy to produce pilot pollution, which is the development bottleneck of massive MIMO system. Compared with the traditional LS and MMS channel estimation algorithms, the LMMSE algorithm based on singular value decomposition, the estimation performance is better and the pilot overhead and feedback overhead are less [6].

By installing dozens or hundreds of antennas at the BS end, large-scale MIMO can simultaneously support a large number of antenna users, among which the number of antennas is greater than the number of antennas of the base station receiver M. users K. Compared with traditional MIMO systems, MIMO systems can improve system connectivity, spectrum efficiency, and energy efficiency. Therefore, massive MIMO technology is proposed as a candidate for 5G in the future.

2. Literature Review. Signal estimation is usually realized by pilot, semi-blind and blind estimation. The blind channel estimation needs to acquire a large amount of signal information, which has high computational complexity and poor real-time performance, and cannot meet the requirements of 5G users with low latency. In semi-blind estimation, the initial values of channel parameters are obtained by a small number of pilots, and the likelihood estimation of complete channel parameters is carried out by signal feedback combined with the posterior information. The method of channel estimation based on pilot frequency is to insert training sequence or pilot symbol which is not carrying useful information and is known to both sender and receiver in the process of signal transmission, and the receiver realizes channel estimation according to pilot frequency signal. Compared with semi-blind estimation and blind estimation, pilot-based signal estimation has the advantages of low complexity and simple method, so it is widely used.

Since the effectiveness of test-based channel evaluation depends on the design and calculation algorithm, many researchers have done a lot of research on the above two factors. Fernandes, P. B. For uncorrelated Ruili fading channel, the optimal signal must be orthogonal and the test length must be equal to the antenna, which is difficult to use in 5G array multiple-input-multiple-output (MIMO) systems [5]. Zheng, R. Z. Channel feedback is used to complete the signal adjustment, which should reduce the interference between the interference signal and the interference signal generated by the receiver, thereby improving the accuracy of channel estimation [20]. Yukun uses the physical connection and proximity of the channel and uses the correlation method to reduce the mean square error of the channel estimation and optimize the test sequence [15]. Deng, X. Adopted the method of channel second-order statistics to allocate pilot frequency, so as to ensure that users using the same pilot frequency correspond to mutually orthogonal channel matrix, thus avoiding the problem of channel pollution [4]. Wang and S. proposed the channel state information feedback scheme of deep neural network based on the channel time correlation, which effectively reduced the channel state information feedback overhead and improved the channel state information feedback accuracy [14]. Sun and W. Z. used sparse channel estimation based on compressed sensing to obtain better channel estimation results, which could better resist pilot interference [11]. Chinnadurai, G. proposed a channel estimation method based on sparse conversion method, which could realize multi-channel parameter estimation under the condition of limited pilot overhead [3].

PSO algorithms were originally developed to simulate bird image quality and unknown motion. From the analysis of animal behavior, the correlation between the information of the group gives the results of the change, which is the basis for the development of the algorithm. The first threshold of PSO was calculated by adding the speed to the neighbors, taking into account the multi-detection and distance speed. Then inertia weights w are introduced to better control effort and search, so the model can be built.

The above pilot design and estimation algorithms are all designed based on small-scale MIMO-OFDM or SISO-OFDM channel system, the dynamic changes of the environment, system overhead and computational complexity in massive multiple antenna systems are not considered, so it cannot be directly extended to massive MIMO systems. Aiming at this problem, the author proposes a channel estimation method for 5G communication system based on improved particle swarm optimization algorithm, in order to reduce the system overhead and computational complexity of channel estimation, the channel estimation model is defined as regression fitting [16]. In order to deal with the dynamic changes of the environment and the inconsistency between the actual scene and the training data, the model is iteratively optimized by the method of online training of small sample data and integrated learning, so as to achieve high applicability of the model. The construction of a wireless communication network consists of three parts: ground stations, transmission stations, and transmission stations that can transmit communications and data around the world. answered. In wireless communication design, channel parity is important to ensure good wireless communication and communication quality. In strong interference and strong interference environment, communication is nonlinear, especially in hybrid MIMO mobile wireless communication, strong interference, it is difficult to know the channel register and channel balance of the communication system.

3. Methods.

3.1. A standard particle swarm optimization algorithm. Suppose I have m particles in a d-dimensional space, and each particle has a position vector and a velocity vector. Each location vector represents a solution. Its position and velocity at the kth iteration are $X_i[k]=(x_{i1}, x_{i2} \ldots x_{id})$ and $V_i[k]=(v_{i1}, v_{i2} \ldots v_{id})$, respectively. The individual and global optimal values recorded by the whole particle swarm during the flight are p_{ibess} and g_{best}, respectively. Under the leadership of p_{itest} and g_{best}, the particle swarm optimizes the whole space. The basic formula of its evolution is (3.1) and (3.2):

$$V_i[k+2]=wV_i[k]+c_1 r_1\left(p_{\text{iks}}-X_i[k]\right)+c_2 r_2\left(g_{\text{best }}-X_i[k]\right) \tag{3.1}$$

$$X_i[k+2]=X_i[k]+V_i[k+2] \tag{3.2}$$

where c_1 and c_2 are the individual and correlation coefficients, respectively, in general; r_1 and r_2 are two numbers equal to 0 and 1. w is the inertial weight used to measure the search and inspection ability of a small object. According to research, the inertia of a weight is often taken as a downward slope. Formula (3.3)

$$w=w_{\max}-\left(w_{\max}-w_{\min}\right)\frac{FEs}{T} \tag{3.3}$$

where $w_{\max}$ and $w_{\min}$ are the initial inertia weight values respectively; FEs is the iteration number of the function; T is the maximum number of iterations with linearly decreasing inertia weight; w remains the same after the number of iterations exceeds T. Usually $w_{\max}=0.9, w_{\min}=0.4$.

3.2. Improved particle swarm optimization algorithm. In the particle swarm optimization algorithm, the individual and the correlation coefficients c_1 and c_2 determine the global and local surveys of the population, respectively, and the following formula (3.4) can be obtained from the deformation of the equation (3.1) according to the data:

$$\begin{aligned} V[k+1] & =wV[k]+c\left\{r_1\left(p_{\text{thest }}-X[k]\right)+r_2\left(g_{\text{bess }}-X[k]\right)\right\} \\ & =wV[k]+c\left(r_1+r_2\right)\left\{\frac{r_1}{r_1+r_2} p_{\text{iteses }}+\frac{r_2}{r_1+r_2} g_{\text{best }}-X[k]\right\} \\ & =wV[k]+ch\left\{h_1 p_{\text{ikes }}+\left(1-h_1\right) g_{\text{best }}-X[k]\right\} \end{aligned} \tag{3.4}$$

where $h=r_1+r_2; h_1=r_1/\left(r_1+r_2\right)$, and the value range of h and h_1 are $[0,2]$ and $[0,1]$ respectively.

If $L[k]=h_1 p_{\text{ikest }}[k]+\left(1-h_1\right) g_{\text{hest }}[k]$ is set, equation (3.5) is:

$$V[k+1]=wV[k]+\mathrm{ch}(L[k]-X[k]) \tag{3.5}$$

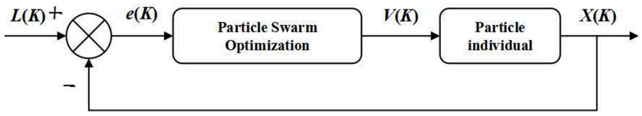

Fig. 3.1: Closed-loop control of Particle swarm optimization algorithm

In the formula, $L[k]$ is the search function of the particle swarm optimization algorithm, and according to the PID control theory, the particle swarm optimization algorithm can be considered as a closed-loop feedback control strategaln the search, $L[k]$ can be regarded as the given value in PID control, while $X[k]$ can be regarded as the feedback value of the system. Each particle can be regarded as the controlled object, namely, the deviation $e(k)=L[k]-X[k]$ of the negative feedback control system, the algorithm obtains the velocity vector of the particle according to the deviation signal, the whole particle swarm flies to the optimal value under the leadership of a given position $L[k](L[k]$ itself contains both individual and global optimal factors). As shown in Figure 3.1:

Substituting equation (3.5) into equation (3.6), we can get:

$$X[k+2]=X[k]+wV[k]+\mathrm{ch}(L[k]-X[k]) \tag{3.6}$$

Take the expectation of both sides at the same time to obtain Equation (3.7)-(3.9):

$$EX[k+1]=EX[k]+wEV[k]+c\left(L'-EX[k]\right) \tag{3.7}$$

Where, $L'=\left(p_{\text{ibest }}+g_{\text{hest }}\right)/2$, (because $Eh=1, Eh_1=\frac{1}{2}$), the following can be deduced:

$$EX[k+1]-EX[1]=w(EX[k]-EX[0])+c\sum_{j=0}^{k}\left(L'-EX[j]\right) \tag{3.8}$$

By transforming equation (3.8) according to the definition of deviation $e(k)$, we can obtain:

$$EX[k+1]=EX[k]+(1-w)Ee[k]+c\sum_{j=0}^{k}Ee[j]+X[1]-wX[0]-(1-w)L' \tag{3.9}$$

That is:

$$EV[k+1]=(1-w)Ee[k]+c\sum_{j=0}^{k}Ee[j]+X[1]-wX[0]-(1-w)L' \tag{3.10}$$

Equation (3.10) shows that it is similar to the discrete PI governing equation, where $K_P=1-w, K_1=c$.

Therefore, PSO can be regarded as a PI controller, V[k] as the output of the controller, and the dynamic characteristics of PSO can be described as Formula (3.11)-(3.13):

$$X[k+1]-X[k]=\Delta X[k]=V[k+1] \tag{3.11}$$

The expression of its discrete domain is as follows:

$$\frac{\mathrm{d}X(t)}{\mathrm{d}t}=V(t) \tag{3.12}$$

Its open-loop transfer function is:

$$G(s)=\frac{X(s)}{V(s)}=\frac{1}{s} \tag{3.13}$$

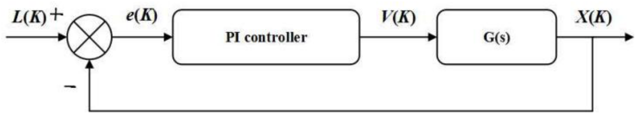

Fig. 3.2: Control block diagram of standard particle swarm optimization algorithm

A control block diagram of the standard particle swarm optimization algorithm is shown in Figure 3.2. The open-loop transfer function of PI controller is shown in equation (3.14):

$$G_{Pl}(s) = K_P + K_l/s \tag{3.14}$$

The closed-loop transfer function is expressed in equation (3.15):

$$\varphi_{PI}(s) = \frac{G_{Pl}(s)G(s)}{1 + G_{PI}(s)G(s)} = \frac{K_P s + K_I}{s^2 + K_P s + K_I} \tag{3.15}$$

Then, the following factors mainly affect the performance of the particle swarm optimization algorithm.

(1) Overshoot, which will affect the search ability of particle swarm optimization algorithm. Large overshoot means large particle search range and strong exploration ability.

(2) Attenuation ratio, a large attenuation ratio represents that the particle will be closer to the optimal value at a larger speed, the search range of the algorithm becomes smaller, but a small attenuation ratio will lead to the particle may be difficult to converge [19, 2, 17].

Usually, taking large scale coefficient and integral coefficient will make the algorithm have large overshoot and small decay ratio. Because the differential coefficient has the function of feedforward control, the overshoot and decay ratio can be reduced, and the differential effect should be reduced or removed in the later stage of the control for the stability of the system [8]. In this way, the convergence speed of the algorithm can be accelerated. The particles fly to the optimal position at a relatively fast speed in the beginning stage, and maintain a good global search ability in the later stage.

3.2.1. Improving policies. According to the above analysis, the particle swarm optimization algorithm is a basic PI controller, on the basis of which the difference between the parameters of the control parameters is shown in the first stage of the algorithm, the ratio of the coefficients and the balance. To improve the speed of rotation of the particle swarm optimization algorithm, small proportions and combinations are brought to the next stage, and the differences of the differences are reduced and the decision differences are shown according to their control. scientific world [13, 10]. The standard equation of its discrete domain is equation (3.16):

$$D[k] = K_D(e[k] - e[k-1]) \tag{3.16}$$

The incremental differential action equation is equation (3.17):

$$\begin{aligned} \Delta D[k] &= D[k] - D[k-3] = K_D(e[k] - e[k-1]) - K_D(e[k-2] - e[k-2]) \\ &= K_D\{(L[k] - x[k]) - 2(L[k-1] - X[k-1]) + (L[k-2] - X[k-1])\} \end{aligned} \tag{3.17}$$

The expression of standard particle swarm optimization algorithm with incremental differential function is equation (3.18):

$$V_i[k+1] = wV_i[k] + c_1 r_1 \left(p_{\text{ib best}} - X_i[k]\right) + c_2 r_2 \left(g_{\text{best }} - X_i[k]\right) + \Delta D_i \tag{3.18}$$

Therefore, the iterative process of improving the particle swarm optimization algorithm is Equation (3.19):

$$\begin{aligned} V_i[k+1] =& wV_i[k] + c_1 r_1 \left(p_{\text{ibest}} - X_i[k]\right) + c_2 r_2 \left(g_{\text{best}} - X_i[k]\right) + K_D\{(L[k] - L[k-1]) \\ & - (L[k-2] - L[k-3]) - (V[k] - V[k-1])\} \end{aligned} \tag{3.19}$$

where $L[k] = \left(p_{\text{itest }} + g_{\text{test }}\right)/2$.

3.2.2. Convergence analysis of improved particle swarm optimization algorithm. Based on equations (3.2), (3.17) and (3.20), we can obtain:

$$\begin{aligned} c_1 r_1 p_{\text{bbest}} + c_2 r_2 g_{\text{best}} = & \left(c_1 r_1 + c_2 r_2 - 1 - w + K_D\right) X_i[k+2] + X_i[k+3] \\ & + \left(w - 2K_D\right) X_i[k+1] + K_D X_i[k] \end{aligned} \tag{3.20}$$

Assuming that the individual and global optimal values of particles remain unchanged, equation (3.21)-(3.23) can be obtained by taking both sides of the equation as expected:

$$\begin{aligned} \left(c_1 p_{\text{ikest}} + c_2 g_{\text{hest}}\right)/2 = & \left(\frac{c_1 + c_2}{2} - 1 - w + K_D\right) EX_i[k+2] + EX_i[k+3] \\ & + \left(w - 2K_D\right) EX_i[k+1] + K_D EX_i[k] \end{aligned} \tag{3.21}$$

After z transformation:

$$\left(z^3 + T_1 z^2 + T_2 z + T_3\right) EX(z) = S \tag{3.22}$$

where $T_1 = (c_1 + c_2)/2 - 1 - w + K_D; T_2 = w - 2K_D; T_3 = K_D; S = \frac{c_1 p_{\text{ibest}} + c_2 g_{\text{best}}}{2} + z^3 X(0) + z^2 [X(1) + T_1 X(0)] + z[X(2) + T_1 X(1) + T_2 X(0)]$.

$z = (u+1)/(u-1)$ is exchanged by linear difference variation, so:

$$Au^3 + Bu^2 + Cu + D = S \tag{3.23}$$

Type, $A = 1 + T_1 + T_2 + T_3; B = 3 + T_1 - T_2 - 3T_3; C = 3 - T_1 - T_2 + 3T_3; D = 1 - T_1 + T_2 - T_3$.

The characteristic equation of equation (3.24) is:

$$Au^3 + Bu^2 + Cu + D = 0 \tag{3.24}$$

As for stability conditions, a system is stable only if the following conditions are satisfied.

$$\left\{\begin{array}{l} A > 0 \\ B > 0 \\ \frac{BC - AD}{B} > 0 \\ D > 0 \end{array}\right. \Rightarrow \left\{\begin{array}{l} c_1 + c_2 > 0 \\ 4 - 4w + (c_1 + c_2) > 0 \\ 2(1 - w)(1 + K_D) + (c_1 + c_2) K_D > 0 \\ 4 + 4w - (c_1 + c_2) - 8K_D > 0 \end{array}\right. \tag{3.25}$$

Under the condition that equation (3.25) is satisfied, the algorithm converges to $\left(c_1 p_{\text{ithest}} + c_2 g_{\text{best}}\right)/\left(c_1 + c_2\right)$, namely equation (3.26):

$$EX(\infty) = \lim_{z \to 1} (z-1) EX(z) = \frac{c_1 p_{\text{ibest}} + c_2 g_{\text{best}}}{c_1 + c_2} \tag{3.26}$$

From the above analysis, it is known that the improved particle swarm optimization algorithm converges under the premise of satisfying equation (3.26).

3.3. Adaptive optimization model for channel estimation. Particle adaptive control and convolution measure extraction of communication signals based on signal and channel analysis, channel equalization is improved.The initial channel estimation model is constructed by training the channel state matrix from a large number of offline data, which is difficult to be used directly in the dynamic channel time-domain environment [9]. In addition, there is a certain relationship between the channel estimation model and the service volume of users, at different time scales (busy and idle), the external interference of channel estimation is also different, therefore, the initial channel estimation model based on offline big data cannot be used for channel estimation in different regions and different time periods, otherwise, its prediction accuracy and performance will be greatly compromised.To solve this problem, the authors optimized the first channel prediction by online training. Since the transmission and reception data are constantly updated, a new channel prediction model is created by training new data, and the weight of the original channel prediction model is changed by comparing the performance of the original channel prediction models. An updated weighted average method is used to adjust the weight of each forecast channel model, and an online performance evaluation model is developed to learn the learning curve of the forecast channel [1]. Those. Figure 3.3 shows the channel prediction optimization model based on online learning.

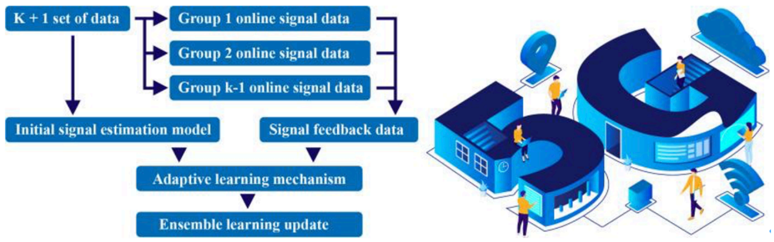

Fig. 3.3: Channel estimation optimization model based on online ensemble learning

Table 3.1: Related channel parameters in simulation experiments

Parameter	Value
Number of subcarriers L	6
The antenna number M	100
Number of users per cell k	$15 \sim 20$
Channel propagation path P	100
Carrier frequency f/GHz	2.5
The wavelength λ/m	0.12
The antenna spacing d/m	0.06
The antenna impedance / Ω	50
Transmission of elevation	[-90,90]
Distance between the user and the base station l_1/m	100
Protection distance between user and base station l_2/m	10
Path loss correlation coefficient	3.8
Number of pilot	$10 \sim 100$
Transmission power of the user terminal P/dBm	-10

3.4. Simulation experiment. In order to verify the author's model, two classical channel estimation methods, LS channel estimation and BLMMSE channel estimation, are compared with the author's model, the channel estimation accuracy of the two scenarios with different SNR and different pilot lengths will be compared. LS channel estimation realizes channel estimation by least square method. BLMMSE channel estimation is to decompose the signal into linear variables, and then realize the channel estimation by least square method. It can be seen that BLMMSE channel estimation can better deal with the problem of nonlinear mapping and has high estimation accuracy.

The relevant channel parameters used in simulation are shown in Table 3.1.

4. Results and Discussion. Comparison of estimation accuracy of three estimation methods under different SNR, Figure 4.1 shows that the main coordinate axis corresponds to the errors of LS channel estimation and BLMMSE channel estimation. The subcoordinate axis corresponds to the channel estimation error. The performance of the channel estimation model is optimal under different channel ratios, with the increase of SNR, the MSE value is stable at about 1200. LS channel estimation and BLMMSE channel estimation methods are not only sensitive to SNR changes, but also have low estimation accuracy at low SNR. This is because in the state of low SNR, the label values corresponding to different channels have little difference, it is difficult to establish an accurate mapping relationship between LS channel estimation and BLMMSE channel estimation when the label difference is small. The authors' model uses online data to continuously optimize the model, an accurate mapping relationship is constructed by iterative method to realize adaptive learning of channel estimation parameters in the scenario of SNR fluctuation [7].

Comparison of the estimation accuracy of the three estimation methods under different pilot lengths, Figure 4.2 shows that the main coordinate axis corresponds to the error of LS channel estimation and BLMMSE channel estimation. The sub-coordinate axis corresponds to the author's channel estimation error. The performance

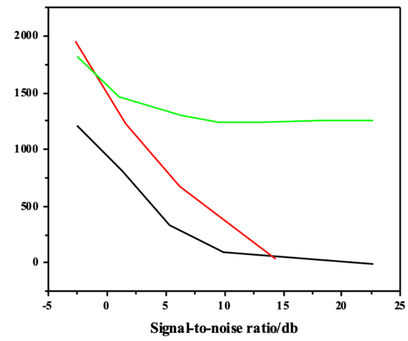

Fig. 4.1: Comparison of estimation accuracy of the three estimation methods under different SNR

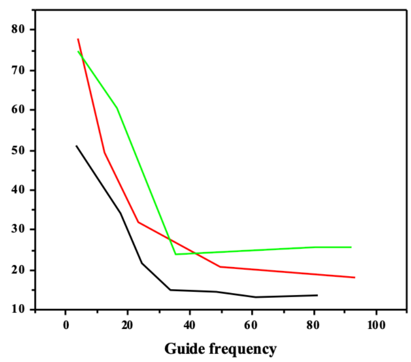

Fig. 4.2: Comparison of estimation accuracy of the three estimation methods under different pilot lengths

of the author's channel estimation model is optimal under different pilot lengths, the LS channel estimation and BLMMSE channel estimation methods are not only relatively sensitive to the change of pilot length, but also when the pilot length, due to the high number of antennas (the number of antennas is 100), its channel estimation accuracy is low. The author divides every five sampling gaps into a data block, when the first data block under each sampling gap is designed as pilot, the other four channel data are estimated by the first data block, in the case of more antennas and low pilot length, the smaller pilot length has little difference, in the case of small tag difference, it is difficult to establish accurate mapping relationship between LS channel estimation and BLMMSE channel estimation [12, 18]. The author's model uses online data to continuously optimize the model and builds an accurate mapping relationship through iteration, which can better cope with the changes of pilot length.

5. Conclusion. In the 5G communication model, channel balance is the key to ensure wireless communication quality and smooth communication. In the environment of strong interference and interference, the communication system has unique characteristics, especially the hybrid MI-MO mobile wireless communication system is prone to strong interference, and thus it is difficult to register the communication channel and achieve channel balance. In this paper, a flame-based fitness monitoring is proposed to test the robustness and performance of the algorithm in terms of signal-to-noise ratio and length difference.

The author introduces channel estimation for 5G communication based on network optimization and divides the channel estimation problem into two problems: regression optimization and online adaptive ensemble optimization. The improved particle swarm optimization algorithm is used to train a lot of data offline, and the first model of the wireless channel is obtained by learning the characteristics of each state of the wireless channel. Based on this, the model was updated with online data, and the modification of the forecast channel was done by the joint method. Finally, the authors create experiments to verify the effectiveness and performance of the algorithm with different SNRs and different lengths. The results show that the method proposed in this paper is the most effective in balancing 5G communication. The error is small, the balance of error is small, the impact is small, and the accuracy of communication has been improved. In conclusion, the channel evaluation method proposed by the authors is feasible and effective.

REFERENCES

[1] F. S. Abdulla, A. N. Hamoodi, and A. M. Kheder, *Particle swarm optimization algorithm for solar pv system under partial shading.*, Przeglad Elektrotechniczny, 97 (2021).
[2] M. Asadi, M. A. J. Jamali, S. Parsa, and V. Majidnezhad, *Detecting botnet by using particle swarm optimization algorithm based on voting system*, Future Generation Computer Systems, 107 (2020), pp. 95–111.
[3] G. Chinnadurai and H. Ranganathan, *Curvature based 2 wheels self supporting robot based on the particle swarm optimization algorithm*, International Journal of Computing & Information Technology, 11 (2019), pp. 37–43.
[4] X. Deng and Y. Lin, *Improved particle swarm optimization for mean-variance-yager entropy-social responsibility portfolio with complex reality constraints*, Engineering Computations, 39 (2022), pp. 1288–1316.
[5] P. B. Fernandes, R. Oliveira, and J. F. Neto, *Trajectory planning of autonomous mobile robots applying a particle swarm optimization algorithm with peaks of diversity*, Applied Soft Computing, 116 (2022), p. 108108.
[6] R. Huang, J. Fan, and H. Tsai, *Application of dormancy particle swarm optimization algorithm based on nonlinear adjustment parameters for maximum power point tracking of photovoltaic arrayy*, International Journal of Electrical Engineering: Transactions of the Chinese Institute of Engineers, 28 (2021), pp. 149–159.
[7] Z. Lin, X. Fu, B. Gu, and Z. Fu, *Retracted article: Groundwater pollution prevention based on improved particle swarm algorithm and sports training optimization*, Arabian Journal of Geosciences, 14 (2021), pp. 1–13.
[8] K. Saplioglu, T. S. K. Ozturk, and R. Acar, *Optimization of open channels using particle swarm optimization algorithm*, Journal of Intelligent & Fuzzy Systems, 39 (2020), pp. 399–405.
[9] J. Shobana and M. Murali, *Adaptive particle swarm optimization algorithm based long short-term memory networks for sentiment analysis*, Journal of Intelligent & Fuzzy Systems, 40 (2021), pp. 10703–10719.
[10] J. Subudhi and P. Indumathi, *Joint user clustering and salp based particle swarm optimization algorithm for power allocation in mimo-noma*, Journal of Intelligent & Fuzzy Systems, 40 (2021), pp. 9007–9019.
[11] W.-Z. Sun, M. Zhang, J.-S. Wang, S.-S. Guo, M. Wang, and W.-K. Hao, *Binary particle swarm optimization algorithm based on z-shaped probability transfer function to solve 0-1 knapsack problem*, IAENG Int. J. Comput. Sci, 48 (2021).
[12] M. Sundaray, A. Tripathy, and S. Tripathy, *A new algorithm based on particle swarm optimization for application in holographic coupler*, Optik, 208 (2020), p. 164551.
[13] B. Urul, *High-gain uwb antenna with optimized metamaterial lens layer via particle swarm optimization algorithm for satellite communication applications*, International Journal of RF and Microwave Computer-Aided Engineering, 32 (2022), p. e23280.
[14] S. Wang, P. Li, H. Ji, Y. Zhan, and H. Li, *Prediction of air particulate matter in beijing, china, based on the improved particle swarm optimization algorithm and long short-term memory neural network*, Journal of Intelligent & Fuzzy Systems, 41 (2021), pp. 1869–1885.
[15] Y. Wang and X. Chen, *Hybrid quantum particle swarm optimization algorithm and its application*, Science China Information Sciences, 63 (2020), pp. 1–3.
[16] S. G. Wardhana and W. Pranowo, *Rock-physics modeling by using particle swarm optimization algorithm*, Journal of Applied Geophysics, 202 (2022), p. 104683.
[17] C. Yong and Y. Lu, *An improved particle swarm optimization algorithm in selection of e-commerce distribution center*, Journal of Intelligent & Fuzzy Systems, 39 (2020), pp. 8783–8793.
[18] L. Zhang, J. Wang, and Z. An, *Fcm fuzzy clustering image segmentation algorithm based on fractional particle swarm optimization*, Journal of Intelligent & Fuzzy Systems, 38 (2020), pp. 3575–3584.
[19] Q. Zhang, Y. Wei, W. Song, et al., *Two strategy cooperative particle swarm optimization algorithm with independent parameter adjustment and its application*, International Journal of Innovative Computing, Information and Control, 16 (2020), pp. 1203–1223.
[20] R. Zheng, Y. Zhang, and K. Yang, *A transfer learning-based particle swarm optimization algorithm for travelling salesman problem*, Journal of Computational Design and Engineering, 9 (2022), pp. 933–948.

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