Improving a machine learning method for an automated control system

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Abstract

The paper is devoted to the improvement of the automated learning management system by integrating the metric proximal gradient method. Improving the automated learning management system helps to increase the efficiency, quality, and safety of the educational process by automating routine tasks and implementing individualized curricula. The paper discusses the use of machine learning to analyze student performance and detect suspicious user activity, which increases the transparency and reliability of the system. The use of the metric proximal gradient method ensures efficient solutions to optimization problems and increases the adaptability of the model in a dynamic educational environment. Also the paper presents an improved approach to automated learning management systems through the implementation of an advanced machine learning method based on the metric proximal gradient algorithm. The research addresses key challenges in educational process management, including system efficiency, quality assurance, and security enhancement. The proposed method incorporates a specialized database for comprehensive event logging and implements clustering and regression algorithms for student performance analysis. The improved metric proximal gradient algorithm demonstrates effective convergence properties through diagonal step sizing and non-monotonic linear search strategies. Results indicate that this approach provides enhanced optimization capabilities for handling complex data structures and adapting to dynamic educational environments. The implementation shows particular promise in personalizing educational routes, optimizing curricula, and maintaining system security through automated anomaly detection.

Keywords

machine learning method, automated control system, metric proximal gradient, educational process

1. Introduction

Improving an automated learning management system (ACS) is an important step towards increasing the efficiency, quality, and safety of the educational process. Automating routine administrative tasks, such as creating timetables, recording attendance, and generating reports, allows you to optimize resource management and reduce staff workload. This allows administrators to focus on more strategic tasks, such as improving curricula and managing the quality of education [1, 2].

Improving the quality of the educational process is one of the key goals of improving the automated control system. The introduction of machine learning technologies allows for more accurate tracking and analysis of student performance, which helps to identify learning problems on time and provide the necessary support. Such innovations also allow for the creation of individualized curricula, which provide a more personalized approach to education, contributing to better learning and improved academic results [3].

The transparency and fairness of the educational process will also benefit from the improvement of the automated learning management system. Automating the assessment and recording of student results reduces the risk of human error and subjectivity, which helps build trust in the system on the part of students and their parents. The transparency of teachers' and administrators' actions provided by automated systems increases the level of responsibility and openness in the educational environment [4].

Improving data security is also an important aspect. In today's cyber threat environment, it is necessary to implement modern authentication and monitoring methods to protect the personal data of students and teachers [5, 6]. This not only reduces the risk of information compromise but also ensures compliance with regulatory data protection requirements. In addition, the use of data for analysis and

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informed decision-making helps the management of educational institutions to identify trends, predict results, and develop strategies for further development.

Improving the ACS also ensures adaptation to modern educational trends, such as distance learning, integration of digital resources, and the use of interactive platforms [7]. This allows educational institutions to remain relevant and competitive in the market of educational services. In addition, improving the usability of the system contributes to the satisfaction of students, teachers, and administration, which is an important factor in creating a positive educational environment [8–15].

Thus, the improvement of the ACS is necessary to ensure an efficient, high-quality, and safe educational process that meets modern requirements and challenges. This not only improves the management and provision of education but also contributes to the overall development of educational institutions in a dynamic world [16–19].

Therefore, the purpose of the paper sis to improve the automated learning management system by introducing an advanced machine learning method [20–23].

2. Research results

The automated control system (ACS) implements a specialized database to store logs of all events occurring in the system. The logs contain information about user authentication, changes in schedules, grades, documents, and other critical operations. Such a database provides high detail and the ability to retrospectively analyze user actions. An important aspect is the ability to sort logs by various parameters (user, subject, document, etc.), which allows the administrator to obtain the necessary information for analysis and decision-making.

Machine learning (ML) in an automated learning management system can be effectively used to analyze student performance. Using clustering and regression algorithms, the system can track the dynamics of the academic performance of individual students or groups. For example, based on historical data on grades, attendance, and assignments, the system can predict the likelihood of successful completion of a course or identify students who need additional support.

In addition, a ‘Decency’ or ‘Integrity’ rating system can be introduced that automatically assigns ratings to students based on their behavior (completing assignments on time, attending classes, etc.). Such ratings can serve as an additional motivational tool for students.

Another important function of ML in an ACS system is to detect suspicious user activity. For this purpose, anomaly detection algorithms are used that can identify deviations from a typical user behavioral pattern. For example, if a user who normally interacts with the ‘timetable’ and ‘grades’ tabs suddenly logs in from another device and immediately accesses confidential documents such as ‘R&D’, the system generates an alarm.

The system can automatically determine the priority level (e.g., critical, high, medium, low) for each incident, depending on the degree of deviation from the norm. With the help of classification algorithms, such events can be automatically filtered and forwarded to the administrator for further investigation. In critical cases, the system can automatically block access to the system from a suspicious device until the circumstances are clarified.

The system also monitors the devices from which the user usually accesses the system. If a new device appears that has not been used before, the system can request confirmation from the user or simply inform the administrator to avoid unauthorized access.

Integration of machine learning into ACS systems significantly increases the level of security and management efficiency. The introduction of such technologies allows for automated tracking of student progress, as well as timely detection and response to suspicious user activity, which contributes to the overall reliability and safety of the educational process.

It is proposed to use the method of metric proximal gradient as a machine learning method.

The algorithm of the metric proximal gradient:

1. Select the starting point $x^0 \in R^n$.
2. Update the metric M^n.

$$y^{n+1} = x^n - \left(M^n\right)^{-1} \nabla f\left(x^n\right)$$

$$x^{n+1} = prox_{q,\mathrm{M}^n}\left(y^{n+1}\right)$$

$$\arg\min_x \left(q\left(x\right) + \frac{1}{2}\left\|y^{n+1} - x\right\|_{M^n}^2 \right)$$

3. If $\left\|y^{n+1} - y^n\right\|_2 \leq \varepsilon$ so, then the algorithm stops. Otherwise, repeat step 2.
4. The study of the choice of algorithm step size to ensure fast convergence revealed that the diagonal step size is more effective than the scalar step size. However, it is necessary to develop clear rules for determining the diagonal step size in convex optimization algorithms.
5. The standard proximal gradient method is guaranteed to converge in sufficiently small steps $\beta < \frac{1}{L}$, provided that f is L-smooth. In this case, without using the Lipschitz constant, it is possible to search over several rows with a return strategy. The methods used in this case guarantee convergence.

6. A non-monotonic linear search on a string allows the objective function $F(x)$ to grow between iterations but leads to a possible decrease in its value. Given the current iteration x^n, the initial metric M^n, and the potential next iteration x^{n+1} check whether the following (M^n, x^{n+1}) criterion is satisfied.

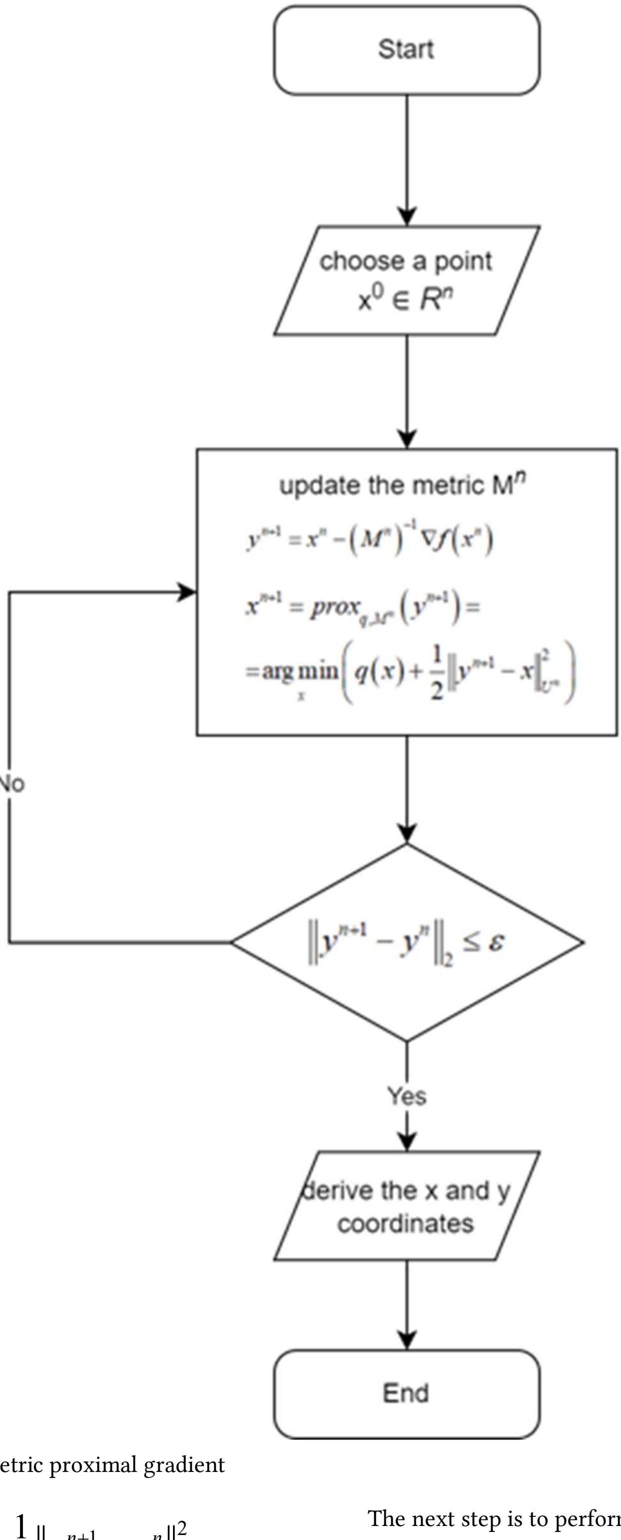

Figure 1: Algorithm of the metric proximal gradient

$$F\left(x^{n+1}\right) \leq \widehat{F}^n - \frac{1}{2}\left\|x^{n+1} - x^n\right\|^2_{M^n}$$

where $K_{LC} \geq 1$ is the search parameter, and $\widehat{F}^k$ is found as follows:

$$\widehat{F}^n = \max\left\{F\left(x^n\right), F\left(x^{n-1}\right), \ldots, F\left(x^{n-\min\left(K_{LC}, n-1\right)}\right)\right\}$$

The next step is to perform a return, changing the scale of the metric M^n with the coefficient $\alpha > 1$.

The next step is to analyze the convergence of the algorithm. Assume that the function *f* is *L*-smooth and $M^n > 0$. The algorithm of the variable metric proximal gradient with diagonal metric will have the following steps:

1. Set the parameters, starting points, and starting metrics.
2. Calculate and by the formula.

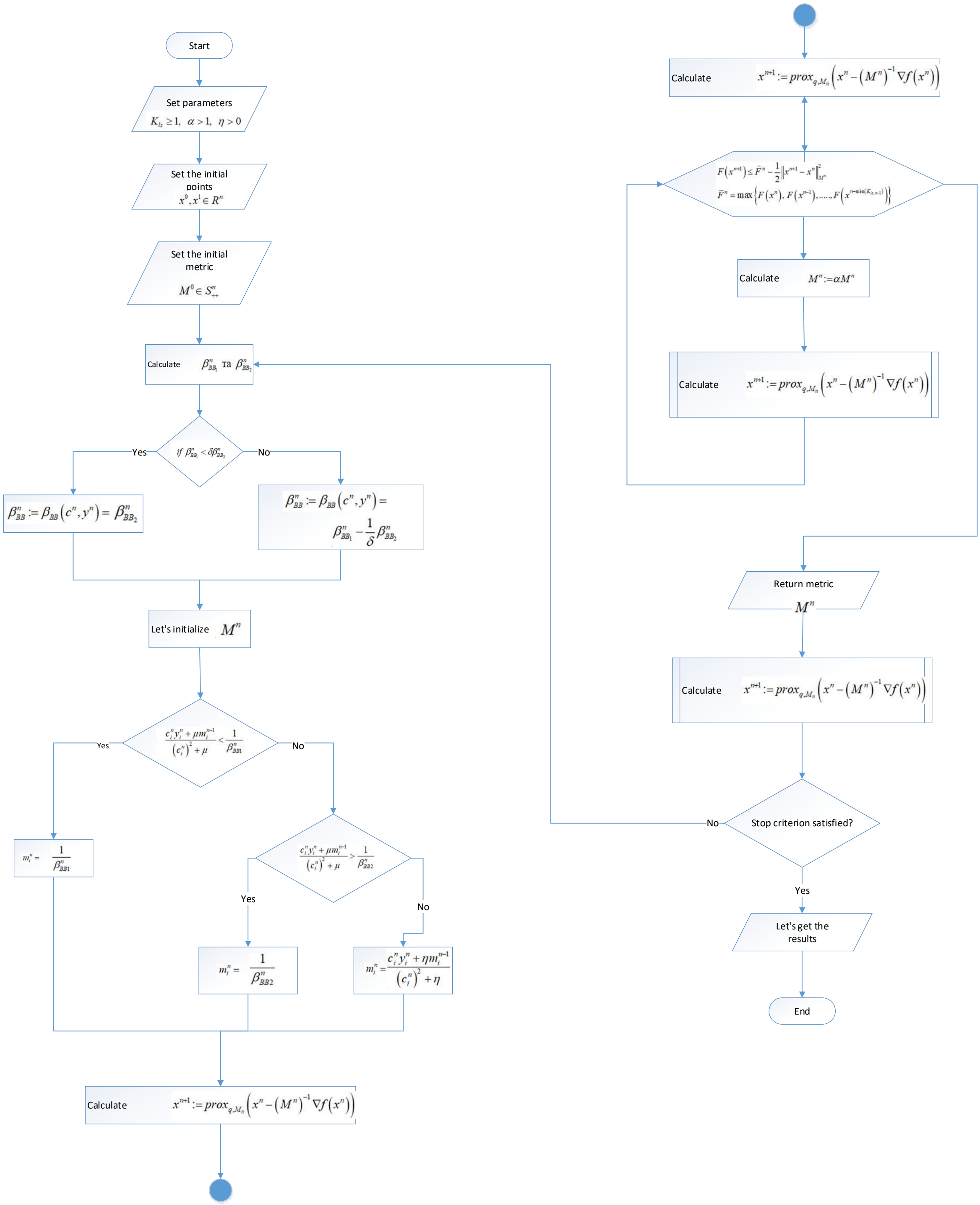

Figure 2: Improved metric proximal gradient algorithm

Set the parameters $K_{ls} \ge 1, \ \alpha > 1, \ \eta > 0$, starting points $x^0, x^1 \in R^n$, and starting metric $M^0 \in S^n_{++}$

Calculate $\beta^n_{BB_1}$ and $\beta^n_{BB_2}$ by the formula

$$\beta^n_{BB} = \beta_{BB}\left(c^n, y^n\right) = \\ = \begin{cases} \beta^n_{BB2}, if \ \beta^n_{BB1} < \partial\beta^n_{BB2} \\ \beta^n_{BB1} - \frac{1}{\delta}\beta^n_{BB2}, in \ other \ cases \end{cases}$$

Initialize M^n according to the formula

$$m_i^n = \begin{cases} \dfrac{1}{\beta_{ББ1}^n}, & \dfrac{c_i^n y_i^n + \eta m_i^{n-1}}{\left(c_i^n\right)^2 + \eta} < \dfrac{1}{\beta_{ББ1}^n} \\ \dfrac{1}{\beta_{ББ2}^n}, & \dfrac{c_i^n y_i^n + \eta m_i^{n-1}}{\left(c_i^k\right)^2 + \eta} > \dfrac{1}{\beta_{ББ2}^n} \\ \dfrac{c_i^n y_i^n + \eta m_i^{n-1}}{\left(c_i^n\right)^2 + \eta}, & \textit{in other cases.} \end{cases}$$

Calculate

$$x^{n+1} := prox_{q,M_n}\left(x^n - \left(M^n\right)^{-1} \nabla f\left(x^n\right)\right).$$

Repeat the expressions

$$M^n := \alpha M^n,$$

$$x^{n+1} := prox_{q,M_n}\left(x^n - \left(M^n\right)^{-1} \nabla f\left(x^n\right)\right).$$

as long as the criterion is met

$$F\left(x^{n+1}\right) \le \widehat{F}^n - \frac{1}{2}\left\|x^{n+1} - x^n\right\|_{M^n}^2,$$

$$\overline{F}^n = \max\left\{F\left(x^n\right), F\left(x^{n-1}\right), \ldots, F\left(x^{n-\min\left(K_{ls,n-1}\right)}\right)\right\}.$$

Return the metric M^n and perform the next iteration x^{n+1}.

Repeat steps 2–6 until the stopping criterion is satisfied

3. Conclusions

The use of the metric proximal gradient method in the automated learning management system (ALMS) is a promising approach to solving optimization problems and improving the system's performance. This method allows you to solve complex optimization problems where conventional gradient methods may be ineffective due to the presence of irregularities or special structures in the objective function. In particular, the metric proximal gradient method effectively copes with sparse or heterogeneous data, which is typical in large educational systems.

Due to its ability to take into account the local geometry of the problem, this method can be used to adaptively tune model parameters, which is especially important in dynamic environments where conditions change over time. For example, it can be used to optimize curricula, personalize educational routes for students, or detect anomalies in user behavior that require immediate response.

In general, the use of the metric proximal gradient method in ACS systems is recommended for tasks requiring high accuracy, adaptability, and efficient processing of complex data structures. This will increase the level of automation, forecast accuracy, and safety in the management of the educational process.

References

[1] V. Buriachok, et al., Implementation of Active Cybersecurity Education in Ukrainian Higher School, Information Technology for Education, Science, and Technics, vol. 178 (2023) 533–551. doi:10.1007/978-3-031-35467-0_32.

[2] V. Buriachok, V. Sokolov, Implementation of Active Learning in the Master's Program on Cybersecurity, Advances in Computer Science for Engineering and Education II, vol. 938 (2020) 610-624. doi:10.1007/978-3-030-16621-2_57.

[3] V. Buhas, et al., Using Machine Learning Techniques to Increase the Effectiveness of Cybersecurity, in: Cybersecurity Providing in Information and Telecommunication Systems, vol. 3188, no. 2 (2021) 273–281.

[4] P. Skladannyi, et al., Improving the Security Policy of the Distance Learning System based on the Zero Trust Concept, in: Cybersecurity Providing in Information and Telecommunication Systems, vol. 3421 (2023) 97–106.

[5] S. Shevchenko, et al., Protection of Information in Telecommunication Medical Systems based on a Risk-Oriented Approach, in: Workshop on Cybersecurity Providing in Information and Telecommunication Systems, vol. 3421 (2023) 158–167.

[6] V. Astapenya, et al., Conflict Model of Radio Engineering Systems under the Threat of Electronic Warfare, in: Workshop on Cybersecurity Providing in Information and Telecommunication Systems, CPITS, vol. 3654 (2024) 290–300.

[7] H. Hulak, et al. Formation of Requirements for the Electronic RecordBook in Guaranteed Information Systems of Distance Learning, in: Workshop on Cybersecurity Providing in Information and Telecommunication Systems, CPITS 2021, vol. 2923 (2021) 137–142.

[8] V. Zhebka, et al., Optimization of Machine Learning Method to Improve the Management Efficiency of Heterogeneous Telecommunication Network, in: Cybersecurity Providing in Information and Telecommunication Systems, vol. 3288 (2022) 149–155.

[9] P. Anakhov, et al., Systematization of Measures on Lightning Protection of the Objects of Telecommunications Network, Int. J. Adv. Trends Comput. Sci. Eng. 9(5) (2020) 7870–7877.

[10] A. Canale, N. Lunardon, Churn Prediction in Telecommunications Industry. A Study based on Bagging Classifiers Telecom, Carlo Alberto Notebooks 350 (2014) 1–11.

[11] DSTU (State standard of Ukraine) 3899:2013. Dyzain i Erhonomika. Terminy ta Vyznachennia Poniat [Design and Ergonomics. Terms and Definitions].

[12] J. Hughes, M. Haran, P. C. Caragea, Autologistic Models for Binary Data on a Lattice. Environmetrics 22(7) (2011) 857–871.

[13] ITU-T Recommendation G.602. Transmission Media Characteristics. Reliability and Availability of Analogue Cable Transmission Systems and Associated Equipments.

[14] A. A. Khan, J. Sanjay, M. M. Sepehri, Applying Data Mining to Customer Churn Prediction in an Internet Service Provider. Int. J. Comput. Appl. 9(7) (2010) 8–14.
[15] O. Klymovych, et al., The Diagnostics Methods for Modern Communication Tools in the Armed Forces of Ukraine based on Neural Network Approach, Modern Machine Learning Technologies Workshop, vol. 2631 (2020) 198–208.
[16] M. J. Wainwright, M. I. Jordan, Graphical Models, Exponential Families, and Variational Inference, Found. Tr. Mach. Learn. 1(1–2) (2008) 1–305.
[17] P. Babarczi, et al., A Mathematical Framework for Measuring Network Flexibility, Comput. Commun. 164 (2020) 13–24.
[18] V. Mukhin, et al., Models for Analysis and Prognostication of the Indicators of the Distributed Computer Systems' Characteristics, Int. Rev. Comput. Software 10(12) (2015) 1216–1224.
[19] W. Kellerer, et al., How to Measure Network Flexibility? A Proposal for Evaluating Softwarized Networks, IEEE Communications Magazine 56(10) (2018) 186–192.
[20] W. Zucchini, I. L. MacDonald, R. Langrock, Hidden Markov Models for Time Series: An Introduction Using R, Chapman and Hall (2016).
[21] Z. Hu, et al., Distributed Computer System Resources Control Mechanism based on Network-Centric Approach, Int. J. Intell. Syst. Appl. 9(7) (2017) 41–51.
[22] V. Zhebka, Modeliuvannia Markivskoho Vypadkovoho Polia z Metoiu Yoho Podalshoi Optymizatsii ta Zastosuvannia, Scientific-Practical Journal Zviazok 5 (2020) 35–40.
[23] V. Zhebka, et al., Methodology for Predicting Failures in a Smart Home based on Machine Learning Methods, in: Cybersecurity Providing in Information and Telecommunication Systems, vol. 3654 (2024) 322–332.