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A machine learning approach for improved shop-floor operator support using a two-level collaborative filtering and gamification features

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Abstract

The increasing gap in shopfloor operators' skillset regarding advanced information and communication technologies along with workforce's diversity require a cognitive system bridging such technical gaps in order to address evolving production demands and satisfy the human need for self-fulfillment and self-actualization at work. This study discusses on a two-level collaborative filtering approach to improve the distribution of information content provided to an operator for completing a manufacturing activity while considering his or her feedback. A prototype implementation is evaluated in a case study related to the operator's job rotation on a shopfloor that involves multiple workstations and tasks.

Keywords: Artificial Intelligence; Operator support; Cyber-physical production system; Gamification; Production

1. Introduction

Manufacturing systems need to constantly evolve to better adapt to changing market's demands and competitiveness. In order to keep pace, technological advances are increasingly incorporated in production systems to support increased levels of flexibility while preserving low production costs. As a result of such technological interventions, conventional production systems are gradually transforming into cyber-physical production systems [1].

The emerging digital transformation that is reshaping production systems will have a significant impact to the working force that will need to be prepared, trained and empowered to cope with the changes and adapt to novel working places [2].

The human capital, however, is often considered by firms as a fixed cost that must be dealt with and flexibility can be achieved only in financial terms, meaning creating or cutting positions. On the other hand, automation can significantly reduce operating costs, endure without the need for rest or compensation. A key difference is caused by the need for increased flexibility and adaptability. Human operators do possess a cognitive learning mechanism. This is not the case with automation systems, yet. In this context, the human factor remains of major importance for a production system, regardless of the penetration of information and communication technologies (ICT) [3].

Considering the human workforce, it is believed that if properly managed and trained under commonly beneficial terms, an evolving human capital could pave the way for a new transformation. In a manufacturing shop floor, context-aware intelligent service systems can be used to provide information services to shop floor personnel, according to their situation [4]. Concerning the aforementioned, and to the fact that each operator may have different learning capabilities and characteristics, this study discusses on a recommendation

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system for factory operators considering the human feedback in the recommendation loop. The integration and evaluation of the workers' feedback are performed towards achieving evolvable and gradually better support in terms of the provided content.

2. Literature review

The factory of the near future could be conceived as a workplace of human-automation symbiosis. A place where human capabilities are enhanced through modern technological advances [5]. In addition, workers can be supported by learning and training approaches, as discussed in [6] where game-based approaches are highlighted for improving the learning curve of students who are being taught factory planning. Moreover, adaptive support is proposed in [7], where a framework for providing real-time decision support is presented useful in case of unexpected events occur and for shopfloor operators. In a similar approach, Nour Nassar in [8] proposes a novel multi-criteria collaborative filtering model based on deep learning. Feature-based rating criteria are used as input in a deep neural network to provide the user with a recommendation.

Recommendation systems have several applications in different domains, such as college libraries [9] or for movies selection out of a database [10]. In particular, recommendation systems can be classified into three main categories; content-based, collaborative filtering, and hybrid with the influence of deep learning approaches being pervasive as discussed in [11]. The first step in a recommendation system and for selecting one piece of information out of a set is the evaluation of similarities between the current set of characteristics or constraints and the ones available in a database or over the internet. Considering the amount of information that a recommendation system may need to process to suggest a recommendation various method have been proposed in the literature. In [12] a deep hybrid collaborative filtering is presented, concerning the recommendation of web services. A deep neural network is used to characterize the complex relations between mashups and services. A method for improving prediction accuracy in recommender systems via a genetic algorithm is introduced in [13]. Also, a genetic algorithm is proposed in [14] for measuring the similarity values between users. Also, an Improving Memory-Based User Collaborative Filtering with Evolutionary Multi-Objective Optimization is discussed in [15].

However, for a system to be human-centred and demonstrate an adaptive behaviour to the human needs, the human input and its analysis remain critical. Thus, the user feedback collection and evaluation along with its role in updating the recommendation is important. In this context, [16] focuses on autoencoders, arguing that would improve the quality of the suggestions by considering also the user's preferences. In [17] and [18], the feedback of the user is indirectly collected. The number of clicks is measured in order to improve the search engine's relevance and user experience. An average precision criterion is proposed for inferencing and analysing the search goals. In addition, negative feedback is considered along with positive in [19]. Both types of user preferences are used for personalizing recommendation engines. However, there has been identified as a certain limit regarding feedback. There is a lack of motivation for the operators for providing quality feedback to the suggestions of a recommendation system. In order to address this limitation [20] proposes gamification features as a solution.

Aim of this study is to extend the work presented in [21], with a two-level Collaborative Filtering (CF) approach. The first level is employed for querying and evaluating the similarity on existing operators' profile, and the second level for retrieving instructions with similar user ratings. Considering the importance of human feedback for the proposed approach, gamification features have been integrated to motivate operators in providing their feedback during runtime.

Finally, the proposed concept has been tested in a use case related to the support of a newcomer operator on a shop-floor with several workstations operating under job rotation principle.

3. Approach

The purpose of the proposed approach is to actively support an operator in runtime by selecting the "best-fit" instruction set considering an assigned task, a specific user profile and his/her execution feedback. The feedback consists of a user-specific evaluation, which is motivated using gamification features, and system feedback. It is assumed that an operator may execute an individual activity multiple times while job rotation is possible. The appropriate instruction is selected through a two-level collaborative filtering approach in combination with a weighted criteria evaluation approach. A high-level representation of the proposed workflow is provided in the following figure (Fig. 1).

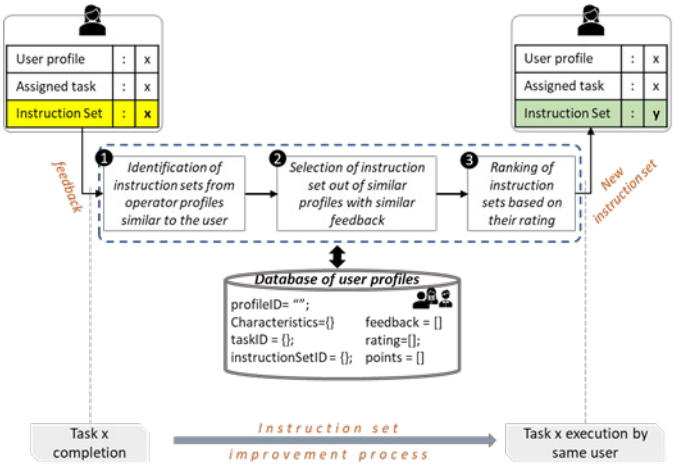

Fig. 1. Concept of the proposed workflow for improving an operator's instruction set based on the a) user and b) system collected feedback.

As discussed in [21], each operator, having a unique profile, can be assigned one or more tasks. A user profile consists of the main entity of associating information related to an operator, such as assigned tasks, skills, etc. Each task is associated with a multi-modal instruction set supporting the operator on how to execute it. Alternative instruction content may be generated by modifying its multi-model content, e.g. with/without audio instructions or different level of detail. Such changes may be a result of personal characteristics, i.e. language, or font size, towards best addressing the operator's needs and preferences. Moreover, modifications may be applied when the operator's performance is less than expected with regards to the production targets. In such cases, the performance of an operator may be improved if an operator with a similar profile, supported with a different instruction set for the execution of the same task performed better, from a production perspective.

Each time an operator executes a task, an instruction set is provided. After the execution of the task, feedback is collected directly by the user (comments, ratings, other), and by the system itself (execution time, language preference, volume, font size, time spent per step, etc.). Those criteria are evaluated by a weighted criteria method, generating for each instruction set a rating. The criteria weights are manually selected depending on whether it would be preferred to prioritize the user satisfaction or the production targets. As such, higher weights may be assigned to production-oriented criteria, such as execution time, or user feedback, expected to achieve higher user satisfaction.

Afterwards, a collaborative filter compares the operator's profile with the existing in a repository database corresponding to the factory or station/line operators. A supervised k-Nearest-Neighbor (KNN) algorithm has been adopted to classify operator profiles to retrieve the ones with similar characteristics to the one under investigation. The KNN algorithm was selected as it is non-parametric, and training can be performed on the test dataset directly. The similarity of the available profiles' is evaluated by calculating the Pearson correlation between the characteristics, such as age, body type, experience, skillset, etc. Thus, the output of the first step of collaborative filtering is a list of similar to the target operator profiles, meaning with similar characteristics and profile properties, e.g. age, nationality, skills, experience, job description, etc.

Following a similar to the first step approach, a second KNN filter is used to identify those similar profiles that received similar feedback. Considering that the feedback received will consider more than one aspects, and a closed-loop control system as the one discussed in this document, will probably modify an instruction set in every turn, the thinking is to investigate whether an operator having provided similar feedback received an instruction set at any point, which outperformed the current set of the target user. The cosine similarity is used in the second step for measuring the cosine of the angle between two profiles' feedback ratings. Instead of finding similar profiles at this step, the purpose is to find other instruction sets that operators of similar profiles rated them higher. In case an instruction set has received no feedback, it is assigned a default value of 0.

As a final step, all instruction sets of operators of similar profile to the under-consideration operator, which provided at some point and for the same task, similar feedback, are compared. The instruction sets are ranked based on their rating. As mentioned above, the rating function is based upon a weighted-criteria method, consisting of the product of system-oriented and user-oriented criteria. The criteria and at the moment of writing this document include the direct user feedback (0-100), the accuracy, understanding and intuitiveness of instructions and from the operator's perspective. In addition, and from the system's or production perspective, it includes the execution time in total for the entire instruction set as well as the time per instruction step, calculated automatically by the system. The rating value is normalized to values between 0 and 1. Finally, the instruction sets are ordered by a ranking function depending on their rating.

A representation of the two-step filtering approach illustrating the similarity-based grouping of the profiles at each step is illustrated in (Fig. 2). As a first step, similar to the user profiles are selected while at the second step the instruction sets of the similar profiles that provided similar feedback are identified.

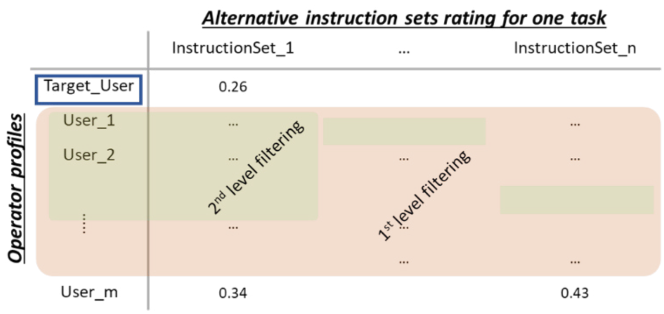

Fig. 2. Profiles filtering using the proposed 2-level KNN approach.

Considering the importance of the user feedback towards a human-centred system capable of addressing the individual needs of modern shopfloor operators, the introduction of gamification features in the aforementioned process was considered. More specifically, each operator profile is associated with a point parameter that depends on the feedback provided. It should be noted that the points depend on user-provided feedback. In turn, the points are associated with virtual badges and status levels, that in turn may be linked to benefits, such as additional break time per 100 points achieved.

4. Implementation

The proposed set of methods and criteria have been implemented into a software prototype following a client-server architecture. The machine learning, analysis, evaluation, and decision-making logic resides on the backend side written in Java and deployed on top of a Tomcat server, version 8 as the existing development.

Moreover, the existing work was extended with some modules written in python. In particular, the KNN modules were developed using the TensorFlow library and python 3.6. For data storage purposes a Cassandra database has been adopted, to facilitate future investigations on large datasets along with experimentation on different machine learning techniques. Data exchange between the backend and the frontend is facilitate using RESTful services. The frontend supports the following main functionalities:

- User registration and authorization

- Task assignment to the user and instruction delivery via a browser and over the internet
- Feedback provision and integration of gamification features
- User profile review including ratings, badges earned, and overall standing in comparison to other users.

The frontend has been implemented using the React.js library as in the previous work [21], while for the gamification features the nodebb-plugin-ns-points library has been employed, supporting a rating bar from 0 to 100 and a 5-star voting option (Fig. 3).

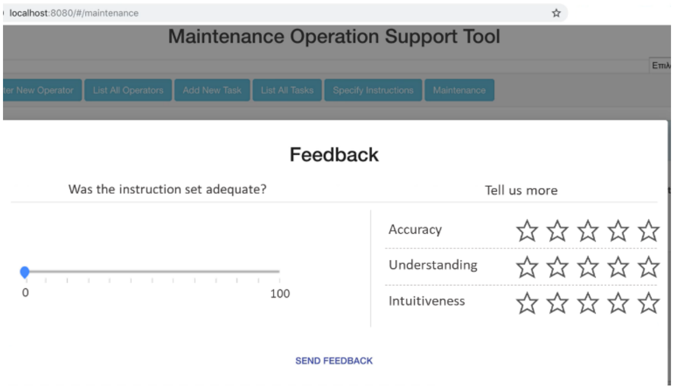

Fig. 3. User feedback interface.

5. Case study

In order to evaluate the potential of the proposed concept, the implemented prototype was tested in a case study related to the job rotation on a shop floor. The scenario involves the following:

- one target user with no previous feedback provided
- 10 operators that have provided previously ratings over the instruction sets.
- 3 discrete workstations where one task can be executed by a single operator.
- 3 screwing tasks with little variation, of approx. 10minutes each.
- Each screwing task includes 3 alternative instruction sets, with content variations. Instruction set 1 includes mainly textual instructions. Instruction set 2 includes mostly video and/or audio, while instruction set 3 is a mix.
- For each operator, a value for her or his feedback is assumed for each instruction set and each task. Moreover, execution time for each user and task based on a given instruction set is provided.
- The first step for providing the target user with an improved instruction set based on his characteristics was to compare his profile to the existing 10 ones. Thus, only the first level of the recommendation system could be used. As a result, and with an average process time of 6 seconds, 4 profiles out of 10 were selected as similar to the target user. The similarity criteria were their age, studies and professional experience.

The ratings of the 4 operators, with different knowledge on how to perform the task are provided in the following table (Table 1), with user 3 corresponding to an experienced operator, users 7 and 10 to average knowledge over the process and 8 to a beginner having performed the tasks for the first time, similar to the target user.

The rating, or else the score, of each instruction set is provided outside the brackets while the execution time for the task is provided within the brackets. As expected, user 3 which corresponds to an experienced operator, which in practice is a student with certain background knowledge on how to execute the activity, achieved the lowest execution time and in most of the samples.

Table 1. Rating (0 to 1) of alternative instruction sets based on feedback collected and completion time per user in minutes inside the brackets.

Task	Users	Instruction set 1	Instruction set 2	Instruction set 3
Task 1	User3	0.45 (8.4)	0.82 (8.1)	0.31 (8.5)
	User7	0.64 (10.1)	0.65 (10.6)	0.16 (10.3)
	User8	0.72 (10.2)	0.54 (11.7)	0.69 (11.3)
	User10	0.57 (9.8)	0.59 (9.4)	0.38 (10.2)
Task 2	User3	0.62 (8.9)	0.72 (9.1)	0.91 (9.5)
	User7	0.67 (9.9)	0.69 (9.8)	0.86 (11.3)
	User8	0.32 (10.6)	0.71 (10.5)	0.72 (10.9)
	User10	0.87 (10.1)	0.82 (9.9)	0.69 (8.9)
Task 3	User3	0.65 (9.8)	0.42 (9.1)	0.90 (9.5)
	User7	0.72 (11.0)	0.62 (9.8)	0.77 (11.0)
	User8	0.23 (9.9)	0.48 (10.3)	0.46 (10.3)
	User10	0.91 (10.1)	0.62 (11.2)	0.31 (10.7)

According to the existing ratings and by evaluating the characteristics of the target user as well as considering a production-wise configured ranking function, the target user is allocated the instruction set number 2 when first executing the Task 1. The assignment is considered as sensible since it received the highest ranking by the most experienced participant with a similar profile to the target user. Moreover, the feedback acquired can be considered as a subjective metric while the completion time measured by the system is rather objective by comparison. Hence, towards providing content that would increase the production efficiency of the shopfloor operators it should be granted a higher weighting value in a system like the proposed one.

After the implementation of the first task, the target user provides feedback to the system and continues with the next task following a similar approach until his feedback is collected for all tasks. During the implementation of each task, the completion time is measured by the system automatically as well as the feedback is evaluated towards awarding points and badges to a user, as part of the gamification features, as presented in the following table (Table 2).

Table 2. Target user's feedback rating per assigned instruction set and task

Task	Instruction set 1	Instruction set 2	Instruction set 3
Task 1		0.79 (10.7)	
Task 2			0.75 (11.1)

Task	Instruction set 1	Instruction set 2	Instruction set 3
Task 3	0.62 (11.6)		

6. Discussion

According to the existing ratings and by evaluating the characteristics of the target user as well as considering a production wise configured ranking function, the target user is allocated the instruction set number 2 when first executing the Task 1. The assignment can be considered as sensible since it received the highest ranking by the most experienced participant with similar profile to the target user. Moreover, the feedback acquired can be considered as a subjective metric while the completion time measured by the system is rather objective by comparison. Hence, towards providing content that would increase the production efficiency of the shopfloor operators it should be granted a higher weighting value in a system like the proposed one.

Regarding the results presented above, it should be noted that the reason for selecting the instruction set 1 for the target user in Task 3 is not clear and further investigation is required. It is assumed that it is caused by the ranking function due to the allocated weights.

7. Conclusion

Recommendation systems are widely used in commercial applications such as search engines and social media. As such this study aims to investigate the potential contribution of such applications in the context of the human-centred cyber-physical production systems.

Therefore, this study discusses on a two-level collaborative filter to enable a recommendation system dynamically adapting to the feedback collected by shopfloor operators and system measurements. It is designed to support two operational models, one towards training the operator and the second towards reducing the production-wise metrics, such as the completion time of a task. A ranking function is in charge of directing the recommendations towards the selected operational mode.

A prototype system was implemented and tested in a use case about the job rotation in a manufacturing system, demonstrating the potential for future investigation and experimentation. The current work demonstrates that a machine learning approach such as the KNN can be used for a recommendation system in manufacturing shop-floor and potentially the cascade connection of multiple KNNs or a similar recommendation or filtering components may support more complex filtering of the results addressing different rapid changing requirements. It should be noted that the KNN algorithm adopted in this study facilitated multiple objectives to be used to filtering the potential outputs.

Next steps will include a larger dataset, experimentation in a laboratory environment as well as the extension of the system with an avatar and the introduction and comparison of the cascade KNN functionality with other machine learning techniques.

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References

[1] Monostori L. Cyber-physical production systems: Roots from manufacturing science and technology. At-Automatisierungstechnik 2015;63:766–76. https://doi.org/10.1515/auto-2015-0066.

[2] OECD. Preparing for the Changing Nature of Work in the Digital Era 2019. https://doi.org/10.1787/888933930573.

[3] Rauch E, Linder C, Dallasega P. Anthropocentric perspective of production before and within Industry 4.0. Comput Ind Eng 2019:105644. https://doi.org/10.1016/j.cie.2019.01.018.

[4] Alexopoulos K, Sipsas K, Xanthakis E, Makris S, & Mourtzis D, (2018) An industrial Internet of things based platform for context-aware information services in manufacturing, International Journal of Computer Integrated Manufacturing, 31:11, 1111-1123, DOI: 10.1080/0951192X.2018.1500716

[5] Romero D, Stahre J, Wuest T, Noran O, Bernus P, Fast-Berglund Å, et al. Towards an operator 4.0 typology: A human-centric perspective on the fourth industrial revolution technologies. CIE 2016 46th Int Conf Comput Ind Eng 2016:0–11.

[6] Bilge P, Severengiz M. Analysis of industrial engineering qualification for the job market. Procedia Manuf 2019;33:725–31. https://doi.org/10.1016/j.promfg.2019.04.091.

[7] Holm M, Garcia AC, Adamson G, Wang L. Adaptive decision support for shop-floor operators in automotive industry. Procedia CIRP 2014;17:440–5. https://doi.org/10.1016/j.procir.2014.01.085.

[8] Nassar, N., Jafar, A., & Rahhal, Y. (2020). A novel deep multi-criteria collaborative filtering model for recommendation system. Knowledge-Based Systems, 187. https://doi.org/10.1016/j.knosys.2019.06.019

[9] Tian Y, Zheng B, Wang Y, Zhang Y, Wu Q. College library personalized recommendation system based on hybrid recommendation algorithm. Procedia CIRP 2019;83:490–4. https://doi.org/10.1016/j.procir.2019.04.126.

[10] Katarya R. Movie recommender system with metaheuristic artificial bee. Neural Comput Appl 2018;30:1983–90. https://doi.org/10.1007/s00521-017-3338-4.

[11] Zhang S, Yao L, Sun A, Tay Y. Deep learning based recommender system: A survey and new perspectives. ACM Comput Surv 2019;52:1–38. https://doi.org/10.1145/3285029.

[12] Xiong R, Wang J, Zhang N, Ma Y. Deep hybrid collaborative filtering for Web service recommendation. Expert Syst Appl 2018;110:191–205. https://doi.org/10.1016/j.eswa.2018.05.039.

[13] Hassan M, Hamada M. Improving prediction accuracy of multi-criteria recommender systems using adaptive genetic algorithms. 2017 Intell. Syst. Conf. IntelliSys 2017, vol. 2018- January, IEEE; 2018, p. 326–30. https://doi.org/10.1109/IntelliSys.2017.8324313.

[14] Alhijawi B, Kilani Y. Using genetic algorithms for measuring the similarity values between users in collaborative filtering recommender systems. 2016 IEEE/ACIS 15th Int. Conf. Comput. Inf. Sci. ICIS 2016 - Proc., IEEE; 2016, p. 1–6. https://doi.org/10.1109/ICIS.2016.7550751.

[15] Karabadji NEI, Beldjoudi S, Seridi H, Aridhi S, Dhifli W. Improving memory-based user collaborative filtering with evolutionary multi-objective optimization. Expert Syst Appl 2018;98:153–65. https://doi.org/10.1016/j.eswa.2018.01.015.

[16] Zhang, G., Liu, Y., & Jin, X. A survey of autoencoder-based recommender systems. Front. Comput. Sci, 2020(2), 430–450. https://doi.org/10.1007/s11704-018-8052-6

[17] Macías-Escrivá FD, Haber R, Del Toro R, Hernandez V. Self-adaptive systems: A survey of current approaches, research challenges and applications. Expert Syst Appl 2013;40:7267–79. https://doi.org/10.1016/j.eswa.2013.07.033.

[18] Leung KW-T, Dik Lun Lee. Deriving Concept-Based User Profiles from Search Engine Logs. IEEE Trans Knowl Data Eng 2010;22:969–82. https://doi.org/10.1109/TKDE.2009.144.
[19] Yin, H., Zhou, X., Cui, B., Wang, H., Zheng, K., & Nguyen, Q. V. H. (2016). Adapting to user interest drift for poi recommendation. IEEE Transactions on Knowledge and Data Engineering, 28(10), 2566–2581. https://doi.org/10.1109/TKDE.2016.2580511
[20] Laurischkat K, Viertelhausen A. Business Model Gaming: A Game-Based Methodology for E-Mobility Business Model Innovation. Procedia CIRP 2017;64:115–20. https://doi.org/10.1016/j.procir.2017.03.051.
[21] Nikolakis N, Stathakis I, Makris S. On an evolutionary information system for personalized support to plant operators. Procedia CIRP 2019;81:547–51. https://doi.org/10.1016/j.procir.2019.03.153.