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Personalized work instruction system for revitalizing human-machine interaction

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Abstract

Diversification of the workforce and machinery has become a forefront issue in advanced manufacturing industries. To respond this challenge, it is necessary to create a sophisticated mechanism in which humans and machines can mutually assist and evolve together for sustainable growth. In this paper, for assembly cell production, we developed work instructions as exemplar “machine” that interact with workers, and analyzed the effect of this interaction on work efficiency. Based on the resulting statistical model, a system that provides personalized machine support for operators was prepared. Fundamental experiments are reported from an application to the assembly of simple mechanical products.

Keywords: Human-Machine interaction; Assembly; Work instruction

1. Introduction

The diversification of labor force in the industry has increased in recent years, due to the aging of the workforce and the mobility of workers across national borders. In addition, advanced technologies such as artificial intelligence (AI) and robot automation are attracting attention, but aging machines are still in operation at factories, thus the diversification of manufacturing equipment is also increasing.

With the advance of digital technology, the gap between human and machine communication is narrowing. However, in reality, there are concerns about changes in the interaction between various people and machines due to the different ages, attributes and skills, and the effects of such changes on society, particularly the working environment.

In an industry-academy collaboration project coordinated by the German Academy of Science and Engineering (acatech), the hypothesis of a new human-machine interaction and the social requirements for realizing that hypothesis are discussed and published in a discussion paper [1]. In order to establish a sustainable society, it is necessary for human to continuously create high value-added jobs and to always be able to shift from obsolete jobs to high value-added ones. Furthermore, it is necessary for the machine to not only carry out low-value-added work, but also to have a mechanism for continuously producing high-value-added work by interacting with human. The paper proposes that human-machine interaction will be activated by a human-centered manufacturing system that fulfills the above requirements.

Furthermore, with regard to the current human-machine interaction (Fig.1 (a)), the above proposal refers to a vicious cycle opportunity assumed as an industrial analogy of the learned non-use phenomenon in the field of brain science [2]. In other words, excessive support from machines may degrade the physical abilities and creativity that humans should originally have, and what should be the interaction between humans and machines in the digital society is something different from now is necessary.

In response to the above issues, the paper addresses the need for a multi-mediation process called *Multiverse Mediation* between human and machines, as a future model for systematically harmonizing their interactions (Fig. 1 (b)). In

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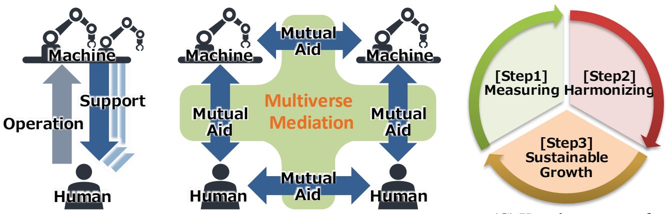
Multiverse Mediation, human-human, human-machine, and machine-machine interactions are coordinated based on a digitized knowledge. The result is a sustainable improvement for both human and machine.



(a) Today (b) Future (C) Key three steps of Multiverse Barrier Free

Fig. 1. Transition of interaction models (a-b) and Multiverse Barrier Free (C).

However, the concept of Multiverse Mediation has not been fully discussed yet. Further discussion is needed on the structure and operation of knowledge sharing, such as how to accumulate knowledge of humans and machines, and how to share the accumulated knowledge at the individual, corporate, and national levels.

As one of the specific procedures for realizing Multiverse Mediation, the concept of *Multiverse Barrier Free* (Fig.1 (c)), is proposed [3]. It is a mechanism to promote sustainable growth by utilizing the diverse characteristics of humans and machines. In this mechanism, following three key steps are defined: (1) Measuring; the characteristics of human-machine interaction are digitalized and a private mediation is created for each interaction., (2) Harmonizing; the mediation generates an appropriate policy of human-machine interactions to compensate for performance bottlenecks, and (3) Sustainable growth; for the purpose of achieving growth in humans and machines, mutual aids need to be provided for each human and each machine. What is important here is that the process has been defined in view of the growth of both humans and machines, but no specific methodology for each step is given.

Considering the growth of humans and machines, it is important to define work capacity as an indicator of growth. Regarding the definition of work ability, the *Work Ability House Model (WAHM)* is proposed by the study of the Finnish Institute of Occupational Health (FIOH) [4]. The WAHM defines various factors that affect the ability of workers at four levels, shaped into a house model. Here, the four hierarchical levels are: (1) health (functional capacity), (2) professional competence (skills, knowledge), (3) values (attitudes, motivation) and (4) work (demands, environment, leadership and management, community, organization). These factors depend on each other, and if any of them are missing or problematic, the house can collapse. It should be noted that not only the physical characteristics (1, 2), but also the psychological characteristics (3) determine work ability. It is also essential to consider the impact of machines that the workers work with, for revitalizing human-machine interaction.

As methods for measuring work ability, big data analysis of body movement [5], heart rate variability [6], questionnaire evaluation of psychological well-being [7] etc. have been proposed. In particular, the evaluation of assembly time has been studied for many years as an evaluation index of assembly work ability. The Methods-Time Measurement (MTM) approach [8] focusing on elementary movements was originally developed in 1948. A similar off-line evaluation method focusing on a physical motion and applied to various industrial fields is the Assembly Reliability Evaluation Method (AREM) [9].

As for the interaction of human workers with their environment, recent studies indicate that the increasing complexity of manufacturing environments and processes expose operators under a heavy cognitive load that may impact their performance and emotions as well [10]. Traditional paper-based work instructions may not support the effective operations in that case as they both take time, and more importantly expertise to apply well. Therefore, the application of multi-modal and digital work instruction systems becomes more common in advanced industrial environments, resulting in better quality, higher effectiveness and performance via advanced was of information distribution [11]**.** Typical multi-modal instruction systems apply video, 3D graphics, voice and even AR solutions to support operators in their work [12].

Challenges for achieving Multiverse Barrier Free include defining an ability model of human-machine interaction, measuring and evaluating physical and psychological data, and structuring and sharing the obtained knowledge. The human ability model is hierarchically defined by WAHM, and can be expanded in consideration of the effects received from machines. Measuring the required data is especially challenging due to the limited number of devices that can be worn or used during working hours. The off-line evaluation methods do not take into account the cognitive load of the operator, so it is not possible to properly measure the perceived task difficulty or the effect on the performance of the operator during assembly [13].

Therefore, a system that covers the entire process from measuring data for ability evaluation to acquiring and sharing knowledge is required. The following sections highlight the focus of this research, present hypotheses and approaches in proof-of-concept use cases, and discuss the details of the proposed method and basic experimental results for simple mechanical products.

2. Approach

This research proposes a systematic solution for acquiring and sharing knowledge in a society where humans and machines are diversified. Especially in this paper, verification of (1) Measuring and (2) Harmonizing of Multiverse Barrier Free concept will be targeted. Knowledge is the codification of past experience and the source of new creativity. This knowledge must be acquired and shared in order to build a sustainable society, with respect to diversity and development of human skills which change over time. In order to construct this mechanism, it is necessary to profile a changing object and knowledge, and to import knowledge according to the object. Additionally, it is required to continuously execute this mechanism. In other words, *dynamic profiling and importing of knowledge* is a key feature of this approach.

To verify this approach, an industrial use case is elaborated. As a subject domain, this paper covers the mass production assembly process in which a variety of unskilled workers enter relatively easily compare to low-volume-multi-product production that requires special skills. As a first step of the research, the process scope is limited to an assembly operation performed by a single operator. In human-centered assembly operations, work instructions were applied that interact directly with workers and affect their performance. In the following part of the paper, a work instruction are referred as one of the *machines*.

In the assembly work that is the subject of this study, the following is hypothesized about the interaction between human and machine:

- In manual assembly, the human abilities vary due to individual characteristics and the difference in machine support, in the form of a work instruction system.
- By optimizing machine support in response to changes in human abilities, the performance of human operators can be maximized.

Assuming a use case that provide optimal training methods for beginners in assembly work, it is necessary to include a consistent process. First, human-machine interactions are modelled from measurement data, then new knowledge is profiled from the model. Finally knowledge is shared between different machines and offered to other people. This process can be represented by the following flow based on Multiverse Mediation.

1. Measuring human reaction with various machines (types of work instructions). It corresponds to profiling multiple human-machine mutual support.
2. Calculate the optimal training method for beginners (step-by-step changes in work instructions) and sharing different machines. It is an example of mutual support between machines.
3. Provide optimal training from work instruction system to beginner workers. This means new mutual support between human and machine have developed.

Through this flow, by profiling various human-machine interactions, machine growth can be realized in the form of an optimal training method. Furthermore, human growth is realized in the form of improving work ability earlier than before with the appropriate support of machines.

3. Proposed methods

3.1. Overview

The proposed method aims to verify dynamic profiling and importing of knowledge through a work instruction system for individuals in the assembly work of a single worker.

A personalized work instruction system has been envisioned as a system to improve work ability by providing optimal work instructions based on a human-machine interaction model to various people, who work in an assembly cell. The overview of the system is shown in Fig. 2. As advance preparation, an interaction model for a combination of various people and machines (here, a plurality of types of work instructions) is constructed, and a work instruction switching logic is defined. Then, in the assembled cell, various sensing data such as work time, change in the heart rate, work operation, and a self-evaluation of emotion are acquired. The real-time mentoring function selects and presents the most appropriate work instruction to the current worker based on the sensing result and the interaction model.

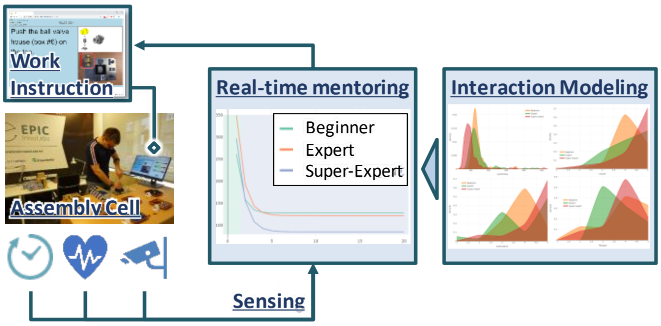


Fig. 2. Personalized work instruction system.

Important here are (1) the experiment environment that acquires sensing data for model construction and real-time mentoring, and (2) a modeling method for constructing an interaction model from the acquired various data. In the following sections, the applied measurement system, experiments and the statistical modeling methods are discussed.

3.2. Implementation of fundamental experiments

The previously mentioned use-case experiment was conducted and the following environment was established (Fig. 3, left). The storage boxes containing the parts of the ball-valve (b) are placed around the jig (a) whilst the operator stands in front of it facing towards the observation unit (e). The manual screwdriver (c) and the storage box for the assembled ball-valves (d) are located on the right side of the jig as well as the touchscreen monitor (f, g) displaying the work instructions (f) and the self-assessment questionnaire of mood – motivation – fatigue (g).

As it was specified in Section 1, the experimental procedure and the proposed method are demonstrated by the assembly of a *¾" MOFÉM AHA ball valve* (Fig. 3, right) consisting of 9 different, and in total 11, parts.

The implemented measuring system used for the experiments is composed of six major subsystems:

1. A dashboard that handles the questionnaire of mood – motivation – fatigue.
2. A Microsoft Kinect depth camera that collects the motion data of the operator.
3. HMIC (Human-Machine Interface Controller) that handles the work instructions [14].
4. A heart rate monitoring device that measures the heart rate of the operator during the experiments.
5. A measurement control laptop that starts and stops the experiments, records the circumstances of the measurement and performs the offline data processing.
6. A central *XML* database that contains all data connected to the experiments.

The communication layout of the overall system is shown in Fig. 4. On the one hand, the work instructions of HMIC are displayed with the help of the laptop that also manages the dashboard. The result of the self-assessment questionnaire is recorded in a *CSV* file, and stored on the same laptop that is responsible for the UI display. On the other hand, the HMIC communicates with the measurement control laptop through HTTP requests (and *NodeRED*) in order to share the relevant information about the ongoing experiments such as the experiment ID, recorded in the main *XML* database by the laptop, and the start and end times of the work instructions, collected in a *TSV* file by the HMIC.

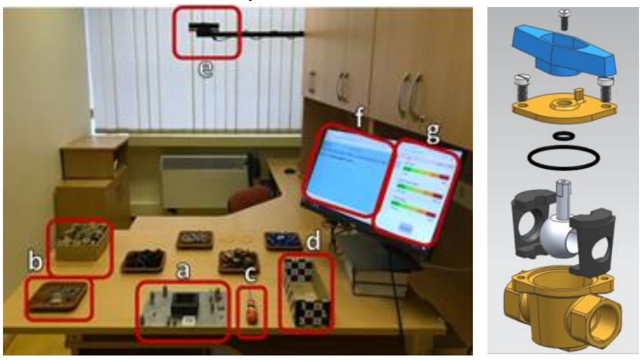


Fig. 3. Experiment environment (left). Assembly product -ball valve- (right).

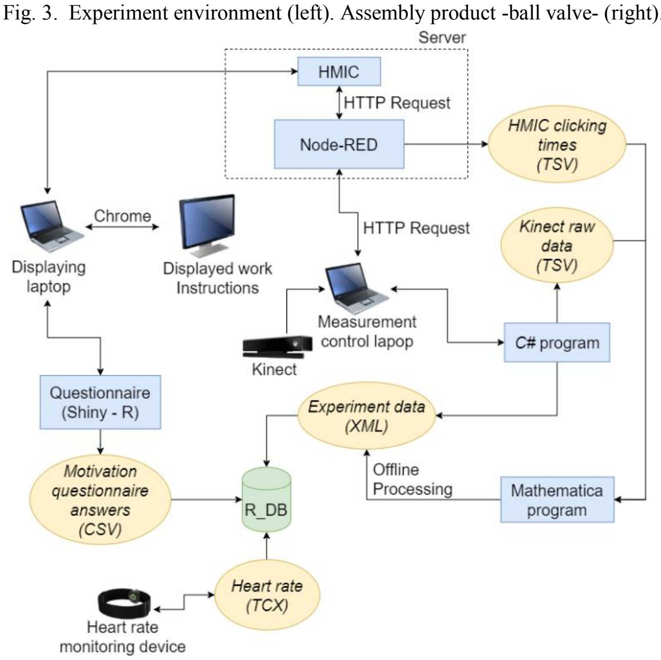


Fig. 4. Measuring system.

3.3. Modeling of human-machine interaction

In this section, an overview of the procedure of modeling the human-machine interaction is discussed from data analytics viewpoint. First and foremost, the initial challenge in any kind of analytics is the integration of data from numerous sources. In such a complex system, as this assembly environment, the measurements are commonly performed by various types of sensors and logging systems. All these separate systems have their own specification and format. Fortunately, many vigorous suitable packages already exist to merge different data sources such as *plyr, pandas* etc. When all data are in satisfying shape, descriptive analytics must be performed, since the deep knowledge of the present variables' meaning and relationship is essential [15].

After performing the necessary pre-analytics, the relevant parameters on the selected KPIs must be identified. Running confirmatory data analysis is an effective method for identification. Statistical hypothesis testing is designed for the comparison of two (or more) data sets [16].

However, selecting the fitting statistical testing method can be a surprisingly challenging question. First, it is always cardinal to distinguish the dependent and the independent variable from each other. Then, the type of each variable must be clearly defined: categorical or nominal, ordinal or rank-ordered, interval or ratio-level. Finally, based on the possible values of the variables and the number of dependent and independent variables, you must choose the suitable hypothesis testing method.

To identify the relevant factors the variables are separated into two groups: independent variables are the personal and environmental attributes (age, height, weather, heart rate etc.), and dependent variables are the KPIs (cycle time, emotional level etc.). Then the KPIs' dependency on the other attributes are investigated by performing the appropriate hypothesis tests (e.g. Kruskal-Wallis or ANOVA test). The null hypothesis is always that the KPI is independent of the independent variable. If we reject the null hypothesis (i.e. the *p*-value of the test is lower than the predefined threshold probability) then the attribute in case is presumed to be a relevant factor.

After collecting all the relevant factors, the optimal sequence of the different work instructions can be determined. Given a new worker and his personal and environmental attributes, he can be assigned to a group with those who are similar to him. Then for each work instruction type a learning curve is calculated based on the historical data of that group. A learning curve can be defined in many ways, e.g. by piecewise linear or exponential curve fitting [16]. With the help of the available learning curves, it is possible to get the optimal sequence of work instructions by choosing the best one at each step.

4. Experiment and discussion

4.1. Fundamental experiments for modeling

The experiments were conducted on different time of the year (summer and fall) and in different hours of the day with 18 volunteers who were working at SZTAKI or were related to SZTAKI members. The following attributes were collected for each person: name, nationality, age, sex, spoken languages, self-evaluated assembly skill on a 5-level scale, height, handedness, palm size, weight and weekly physical activities in hours. The gender, age, handedness and height distribution of the participants can be seen in Fig. 5. During one experiment the operator assembled 20 ball valves, so that in total there were 360 assemblies.

In addition, not only the human side, but also the machine side had different attributes, and their combinations were altered in the experiments. As for the jigs, experiments were conducted with and without jig, however this analysis focuses on the cases with jig. As for work instruction, three different types (*Beginner/Expert/Super-Expert*) were defined. The Beginner work instruction type consists of 13 step-by-step tasks. Each task contains one work piece placement or replacement instruction. The Expert type contains more concise tasks. One task in Expert equals to one to three tasks in Beginner. In total, the Expert contains 5 tasks. The Super Expert work instruction type includes only one compendious task with all the steps.

At the beginning of the conducted experiments the operators were asked about their personal information. After these attributes were collected on the measurement control laptop (Fig. 4) by the observer, the volunteers were asked to answer the self-assessment questionnaire of mood, motivation and fatigue. They were also informed about the process of the measurement and were guided which work instruction type are they required to choose based on random assignment and they used the same type during the whole experiment. After finishing an assembly consisting of 1, 5 or 13 tasks, depending on the work instruction type, the correctness of the ball valve had to be checked, and the aforementioned questionnaire was answered again. Finally, with clicking on the "Start again" button, the next ball valve assembly cycle was started with the previously chosen work instruction type. To simulate the breaks at work, after 10 assemblies the operators had a 5-minute-long break. After the 20th assembly, the experiment was completed.

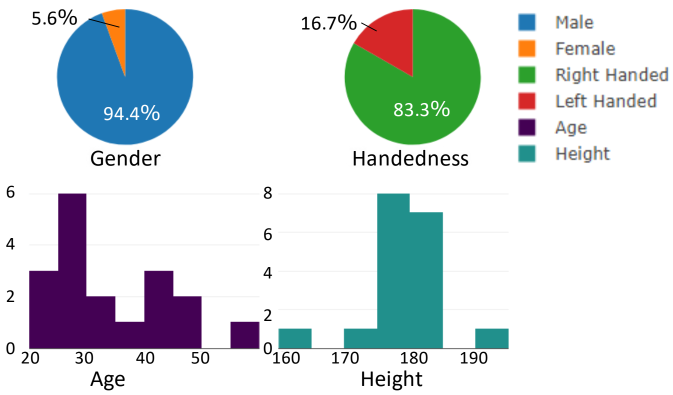


Fig. 5. Attributes distribution of the experiments.

4.2. Modeling results

The way of obtaining personalized work instructions from experimental data is discussed here step by step. After the sample is grouped by instruction types, significant diversity exists among the cycle times (CT) (Fig. 6). To identify the relevant factors on the chosen KPIs (CT and emotion levels), Figure 7 shows the results of the performed hypothesis tests. As mentioned before, small p-values indicate high relevance, therefore dark areas are considered to be the interesting ones. The type of work instruction is seemingly an important factor, it influences the distribution of every KPI (Fig. 8). By fitting exponential functions [17] on the grouped CTs, the optimal sequence of work instructions is defined by choosing the one with the best results at every time point (Fig. 9).

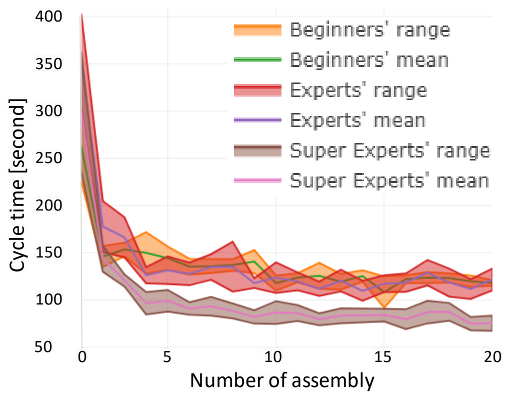


Fig. 6. Statistics of cycle times (CT) separated by instruction type. The width of the ribbons is equal to the deviation of CTs.

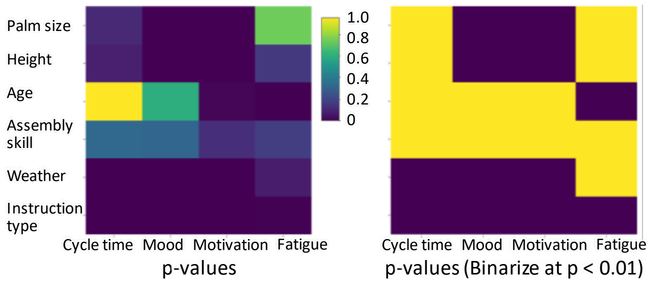


Fig. 7. P-values of different hypothesis tests (left) and the most relevant pairs highlighted (right). Independent variables are on y axis, dependent variables are on x axis.

Fig. 8. Different distribution of CT, mood, motivation and fatigue grouped by instruction type. Y axis shows density.

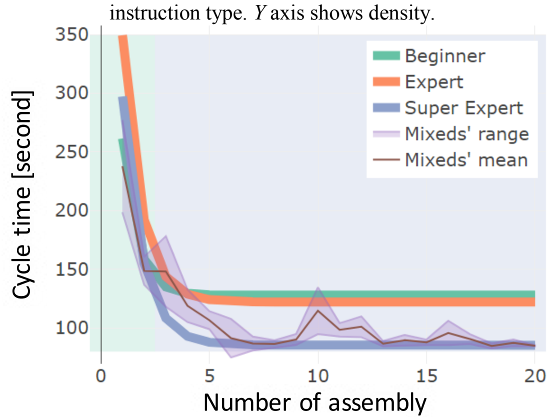


Fig. 9. Learning curves grouped by instruction type on every participant. The color of background represents the instruction type with the best performance for each assembling process.

In case of uncertainty, when marginal differences occur, it is necessary to consider the possibility of not choosing the instruction with the theoretically best KPI. Since switching between instruction types might cause the worker some level of confusion, balancing the frequency of switching must also be kept in mind. Optimization is a solution for this problem, with certain constraints, e.g. the highest-level instruction is disqualified for the first few occasions. Also, introducing penalty of switching induce fewer changes between instruction types. Therefore at the second time point Beginner instruction is preferred to Super expert in this experiment.

4.3. Verification experiment and discussion

As a result of analyzing cycle time and emotion level as key parameters for modeling human-machine interaction, it was confirmed that the work instruction type affected all KPIs. Based on the modeling results, the optimal work instruction switching timing (here, switching to *Super-Expert* from the third time) could be profiled as a new knowledge that the machine should have to import to the person who performs the work for the first time.

Figure 9 shows not only the learning curves of the three instruction types, but also the cycle times of an experimental *Mixed* scenario (4 different workers assembled 80 ball-valves addition to fundamental experiments in Section 4.1). Even though the implementation of the previously discussed results is under process, this *Mixed* sequence of instructions was inspired by engineering intuition. It starts with two steps of *Beginner*, then three steps of *Expert*, and ends with fifteen steps of *Super expert* guidance. The CTs here stayed more or less below the learning curves.

Through this verification, the ability of people to improve over time was measured, and it was confirmed that profiling of new knowledge and importing knowledge could further improve the ability. In the meanwhile, it was not possible to find the relationship between personalized parameters and work instructions. Most probably this is resulted by the fact that subjects are all belong to the same research institution (sampling was not representative), and that the ball valve to be assembled is too easy to assemble. In this regard, the effects of personalized work instructions have not yet been verified, and further verification is needed in the future.

5. Conclusion and future works

In this study, an approach of dynamic knowledge profiling and importing was proposed to realize a sustainable society in the diversification of human and machine. In order to realize this approach, assembling work, in which the inflow of various human resources is expected to progress relatively easily, is selected as a use case showing a specific example of human-machine interaction. For this use case, the feasibility of an integrated system from data measurement to knowledge acquiring and sharing was verified through the development of the personalized work instruction system. Human-machine interactions were modeled from fundamental experiments combining human attributes and work instruction types. The effect of switching work instructions optimally based on this model was verified by experimental scenarios. However, profiling of knowledge about human-specific attributes in a limited experimental environment has not been achieved.

As a future plan, the feasibility of this system and the validity of the proposed approach will be verified in a diversified actual manufacturing site where a complex product with a larger number of parts than a ball valve is assembled.

Acknowledgments

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References

[1] Kagermann H, Nonaka Y, Revitalizing Human-Machine Interaction for the Advancement of Society, acatech DISCUSSION, 2019.
[2] Taub E, Uswatte G, Elbert T, New Treatments in Neurorehabilitation, Founded on Basic Research. In: Nature Reviews Neuroscience. 3(3): 2002, pp. 228-236.
[3] Hitachi Brand Channel: Multiverse Barrier Free – Revitalize Human-Machine Collaboration. Online Video on YouTube, 2019. URL: https://www.youtube.com/watch?v=fKjN3PPbUhk [as at: 31.01.2020.]
[4] Ilmarinen J, Tuomi K, Past, Present and Future of Work Ability. Finnish Institute of Occupational Health, People and Work, Research Reports; 2014. 65. pp. 1–25.
[5] Yamagiwa S, Kawahara Y, Tabuchi N, Watanabe Y, Naruo T, Skill grouping method: Mining and clustering skill differences from body movement BigData. In 2015 IEEE International Conference on Big Data; pp. 2525-2534.
[6] Kunimasa S, Seo K, Shimoda H, Ishii H, An Estimation Method of Intellectual Work Performance by Using Physiological Indices. Global Science & Technology Forum (GSTF); 2017. pp. 111-117.
[7] Johnson S, Robertson I, Cooper C L, Well-being: Productivity and Happiness at Work. Palgrave Macmillan, 2nd edition, 2018.
[8] Delmar WK, Franklin HB, Engineered Work Measurement. 4th edition. Industrial Press, 1987.
[9] Suzuki T, Ohashi T, Asano M, Arai T, Assembly reliability evaluation method (AREM). CIRP Annals; 2003. 52(1). pp. 9-12.
[10] Lušić, M, Fischer C, Bönig J, Hornfeck R, Franke J, Worker information systems: State of the art and guideline for selection under consideration of company specific boundary conditions. Procedia CIRP; 2016. 41. pp. 1113-1118.
[11] Keller T, Bayer C, Bausch P, Metternich J, Benefit evaluation of digital assistance systems for assembly workstations. Procedia CIRP; 2019. 81. pp. 441-446.
[12] Vernim S, Gunther R. Usage frequency and user-friendliness of mobile devices in assembly. Procedia CIRP; 2016. 57. pp. 510-515.
[13] Alan C, Errol H, Cally C, Subjective estimates of times for assembly work. International Journal of Industrial Ergonomics; 2017. Volume 61. pp. 149-155.
[14] Kardos Cs, Kemény Zs, Kovács A, Pataki B, Váncza J. Context-dependent multimodal communication in human-robot collaboration. Procedia CIRP; 2018. 72. pp. 15-20.
[15] James G., Witten D, Hastie T, Tibsharani R, An introduction to statistical learning. New York: springer; 2013. Vol. 112, pp. 18.
[16] Montgomery DC, Runger GC, Hubele NF. Engineering statistics. John Wiley & Sons, 2009.
[17] Li Y, Yang X., Yang Z, Uncertain learning curve and its application in scheduling. Computers & Industrial Engineering; 2018.
[18] Anderson JE, A theoretical foundation for the gravity equation. The American economic review; 1979. 69(1). 106-116.