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CONCEPTUAL FRAMEWORK FOR PROVIDING MANUFACTURING UX USING CONTEXT AWARENESS AND DUAL REALITY

Minseok Kim[1], Sung Ho Choi[1], Kyeong-Beom Park[1]
Jae Yeol Lee[1,*] and Yong-Ju Cho[2]

[1]Department of Industrial Engineering
Chonnam National University
77 Yongbong-ro, Buk-gu, Gwangju 61186, Korea
kimminseok109@gmail.com; { pkb1108; zofmzownldj }@naver.com
*Corresponding author: jaeyeol@jnu.ac.kr

[2]Korea Institute of Industrial Technology (KITECH)
89 Yangdaegiro-gil, Ipjang-myeon, Seobuk-gu, Cheonan 31056, Korea
yjcho@kitech.re.kr

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Abstract. *Various manufacturing information and user contexts must be simultaneously considered to provide user-centric services such as real-time monitoring, 3D visualization, and remote collaboration in the smart factory environment. This paper presents a new conceptual framework for providing smart manufacturing user experience (UX) using AR/VR-based dual reality and machining learning-based context awareness. In the back-end, manufacturing contexts will be analyzed and learned through machine learning, and in the front-end, dual reality-based visual information through AR/VR will be provided for user-centric manufacturing UX. Therefore, users can perform various tasks more effectively and collaborate with each other more naturally, which can build a new manufacturing service system, a customized production environment.*
Keywords: Manufacturing service, Augmented/virtual reality, Context-awareness, Manufacturing user experience (UX), Machine learning

1. **Introduction.** The key word for Industry 4.0 in Germany is the 4th Industrial Revolution, which is to build a new manufacturing ecosystem (e.g., Smart Factory) through the fusion of manufacturing services and information communication technology (ICT) [1]. A new manufacturing ecosystem refers to a customized production environment that can incorporate ICT technology into the existing manufacturing services to effectively and actively reflect the user's requirements on the product. In addition, the universalization of smart and wearable devices has made it easier for users to receive various types of manufacturing information regardless of their locations.

In a manufacturing system, it is essential for the worker to recognize the situation of the task more quickly and accurately in order to perform it effectively. It is also necessary for him/her to make appropriate decisions based on the perceived situation. This is very important because it is related to safety as well as productivity. Therefore, in order to recognize the situation in the manufacturing system and to support proper decision making, the user must acquire and utilize various complex knowledge about the entire process of the manufacturing system or the specific task.

However, because the manufacturing environment or situation changes dynamically, it is difficult for the user to accurately perceive various situations within the manufacturing environment, and it is more difficult to memorize all of the knowledge to cope with it. Thus, it is essential to provide a viable way or method for the user to effectively adopt to the rapidly changing environment through context-aware visualization and interaction behavior. In particular, a new approach to manufacturing UI/UX technology is needed to recognize the user's situation and to reconfigure it as meaningful information [2,3].

In the manufacturing industry, if the information or interface required by the user is mis-designed or misunderstood, there may be serious problems in safety or work efficiency. Therefore, providing effective and intuitive UI/UX to the user is an important factor for enhancing productivity and convenience. Among the widely known UI/UX technologies, virtual reality (VR) or augmented reality (AR) can provide users with high immersion and realism for visualizing manufacturing services. Thus, various efforts are being made to apply it to manufacturing industries [4,5]. However, in manufacturing sectors, AR/VR is mainly used to provide static or limited manufacturing information to users [6]. This information cannot be considered to be user-centered or context-aware. For this reason, there are many restrictions in providing situation-aware manufacturing experience.

Consequently, in the real manufacturing environment, different types of manufacturing information and user contexts must be simultaneously considered to provide user-centric manufacturing services such as real-time monitoring, 3D visualization, and interaction. Unfortunately, there is few previous work to deal with these necessities. This paper presents a new technology framework for providing smart manufacturing user experience (UX) using AR/VR-based dual reality and machining learning-based context awareness [7]. In the back-end, manufacturing contexts will be analyzed and learned through machine learning, and in the front-end, dual reality-based visualization and interaction using AR/VR will be provided for user-centric manufacturing UX. Therefore, the proposed approach can provide a basis to build a new manufacturing ecosystem, a customized production environment. This paper is organized as follows. Section 2 reviews related work, and Section 3 overviews the proposed approach and presents the manufacturing UX framework and relevant scenarios. Section 4 shows how the context-awareness and AR/VR can be combined to provide manufacturing services. In Section 5, conclusions and future research directions are presented.

2. **Related Work.** In the manufacturing system, several research works were conducted to obtain the necessary information in the process of performing a task and to support the effective task execution by utilizing it. In particular, augmented reality was widely used for UI/UX to provide users with effective visual information in the physical working area. In addition, mobile devices and wearable devices were utilized to allow users to work and move more naturally and freely.

Webel et al. [8] proposed an AR-based training platform for assembly and maintenance skills that could accelerate the technicians' acquisition of new maintenance procedures and improve the adjustment of the training process for new training scenarios. They also analyzed the use of augmented reality and multiple modalities for general purpose training. Michalos et al. [9] presented an AR tool for supporting operators where humans and robots coexisted in a shared industrial workspace. The AR tool provided the visualization of the assembly process, video and text-based instruction status updates. Thus, it could enhance the operator's safety and acceptance of hybrid assembly environments through the immersion capabilities of AR technology. Liu et al. [10] proposed an AR-assisted intelligent window for a cyber-physical machine tool. The intelligent window was composed of four main functional modules such as real-time control, AR-enabled process monitoring, AR-enabled machining simulation, and process optimization. Sun et al. [5] proposed the usage of an AR solution to bridge the existing semantic data and information with the real-world physical objects. They found that their approach was highly practical, benefited from its independence of external sensors, markers, and the capability of handling complex environments and changing objects. Wang et al. [11] proposed a human cognition-based interactive AR assembly guidance system to investigate how AR could provide various modalities of guidance to assembly operators for different phases of user cognition process. Filho et al. [12] described an architecture designed to support contextual and mobile applications in the industrial domain and the application of this architecture in the development of the MyWorld application, a contextual mobile application that worked as a single point of entry for a field engineer's needs.

In most previous research works, to provide users with relevant and right information on related tasks and machines in a manufacturing system, an ontology-based database was constructed, and necessary information corresponding to the working situations was retrieved and provided to users. However, manufacturing services in the existing research provided only static information to users without considering user's situation (location, task, technology level, etc.). Thus, the information could be misunderstood and thus this could cause the productivity and safety problems. Therefore, in this paper, we analyze and recognize the user's situation by using machine learning to provide user-oriented manufacturing services. In addition, by using dual reality based on AR/VR, the manufacturing information can be more vividly visualized and reconstructed depending on the user's situation.

3. **Overview of the Proposed Manufacturing UX Framework and Realization.** This research aims to develop a conceptual but challenging manufacturing UX framework through context-awareness based on machine learning and visualization and interaction based on AR/VR-based dual reality. As shown in Figure 1, this framework can provide appropriate and meaningful manufacturing information by filtering and analyzing the structured and unstructured data related to user situation through machine learning. In addition, by reconfiguring this information to the user's situation, it is possible to provide user-centric visualization, interaction, and collaboration through dual reality based on AR/VR. This framework includes the following key characteristics.

- Machine learning-based context awareness: correctly analyzing and recognizing user's situation, task, and manufacturing information, and deriving user-centric manufacturing information
- AR/VR-based dual reality: providing dual reality-based information visualization with integrated AR and VR to support users to effectively perform complex tasks
- Dynamic and natural user interaction: minimizing the visual cognitive burden of the user by providing a dynamic visual reconfiguration suitable for the user's situation, and providing a natural interaction using the user's bare hands

Based on the proposed manufacturing UX framework, we can provide appropriate user-centric manufacturing services. Figure 2 shows a possible scenario for these services. Whenever a user requests a manufacturing service, the system analyzes the situation of the user through user contexts, devices and sensors attached to the user or tool. In addition to the user contexts, the system searches for the necessary manufacturing information through the machining learning-based classification or matching. Based on both knowledge, it dynamically generates user-centric visualization through dual reality. Depending on the manufacturing situation, VR or AR or hybrid reality can be provided to the user. Furthermore, the user can interact with the smart devices through natural user interaction such as multi-touch or hand gesture.

Regarding context awareness and knowledge acquisition, the existing ontology-based method requires a huge amount of information gathering and correlation between information, while the machine learning method extracts the correlation or pattern between information itself through repetitive learning [6]. However, previous context awareness application in manufacturing services mainly focused on the analysis of static statistical data without regarding user situation. Thus, there was a difficulty in providing a user-centric manufacturing UX. On the other hand, this research tries to utilize deep learning algorithms [7] such as CNN (Convolutional Neural Network) or RNN (Recurrent Neural

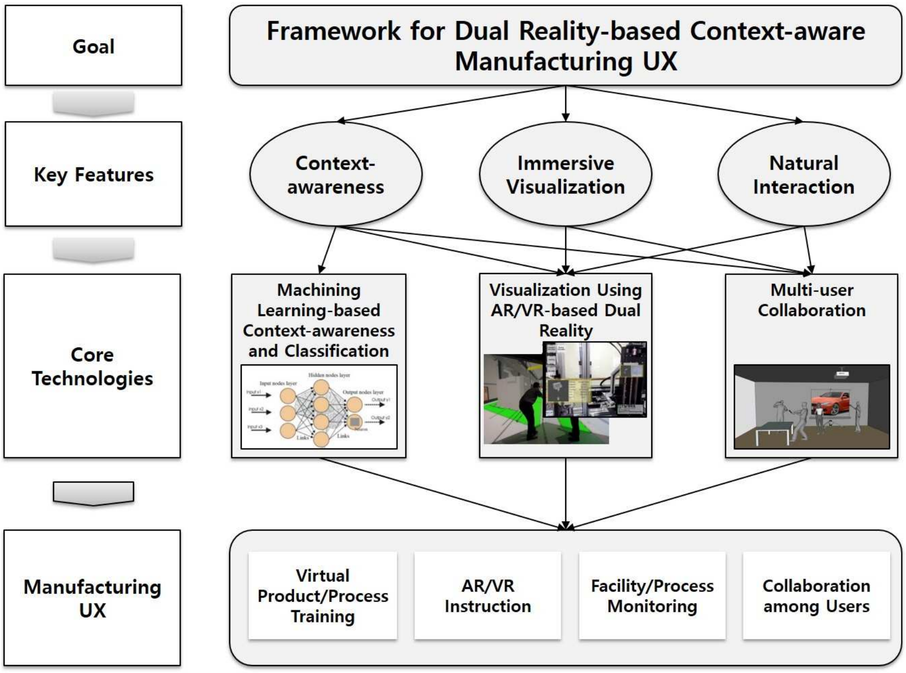

FIGURE 1. Proposed framework

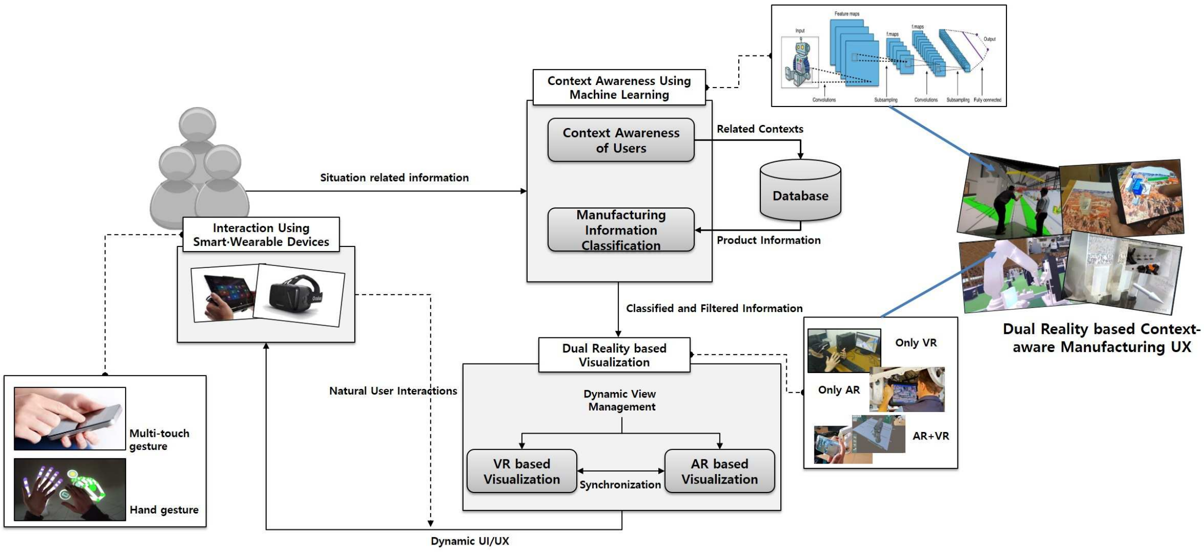

FIGURE 2. Scenario for context-aware manufacturing services

Network), which can perform more precise user situation recognition by analyzing unstructured data such as image or video that can be obtained not only from formal data but also from smart wearable devices and sensors of workers as shown in Figure 3.

4. **Context-Aware Manufacturing Services and System Implementation.** In the manufacturing environment, the user must be aware of various manufacturing situations and perform tasks using the necessary situational information. However, it is very difficult for the user to remember all the necessary information and knowledge about complex tasks. Accordingly, it is necessary to acquire only the necessary information in real time according to the manufacturing environment and the user's situation.

In this research, a machine learning technique is used together to recognize the manufacturing environment and situation for structured and unstructured data (image, mobile

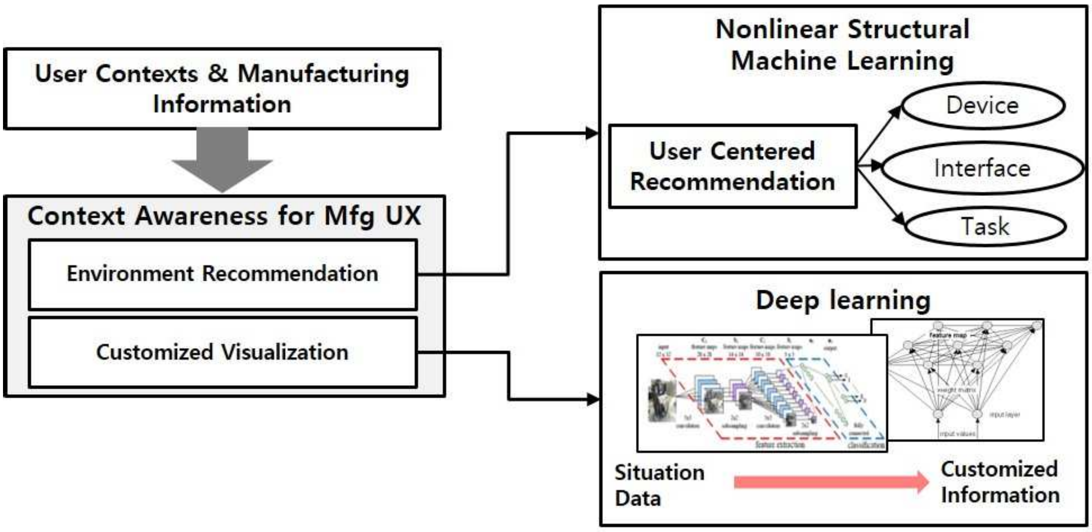

Figure 3. User-centric manufacturing services using machine learning

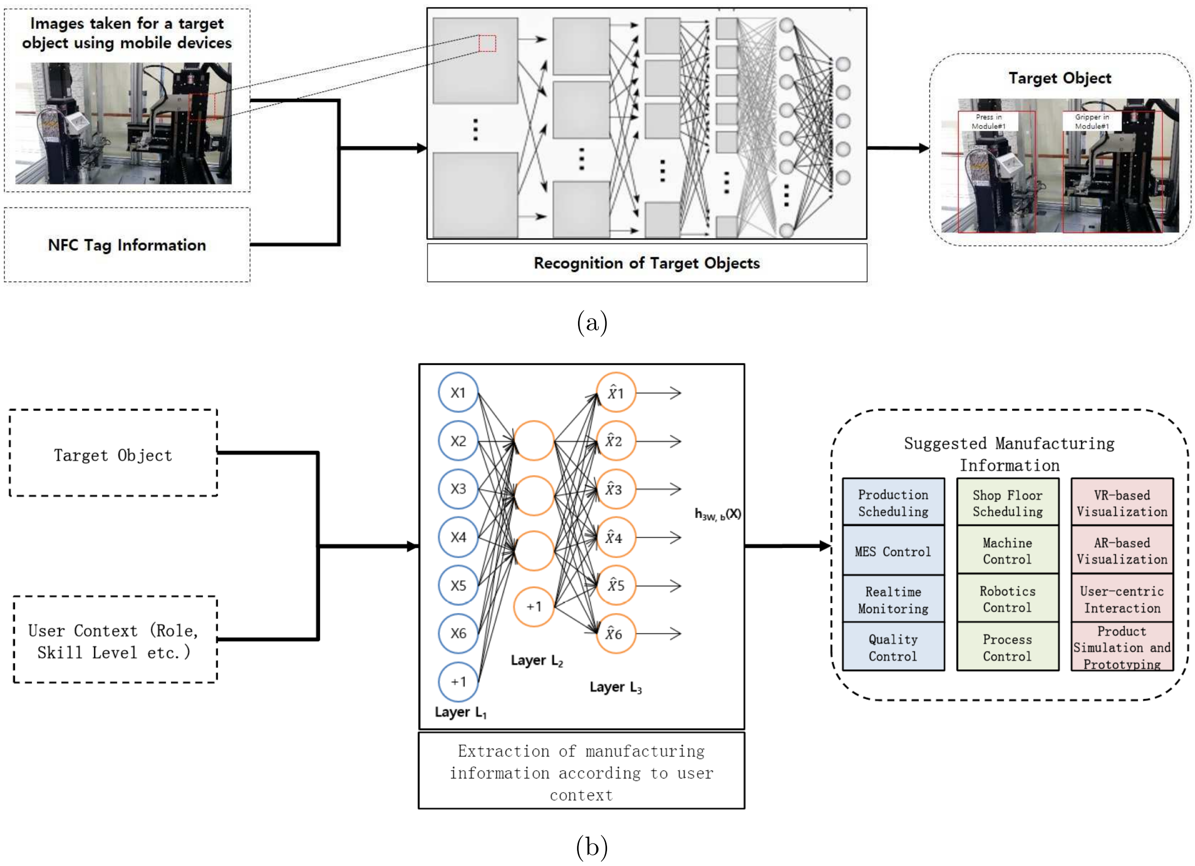

Figure 4. Machine learning based context awareness: (a) target object recognition, (b) context-aware manufacturing information extraction

device sensor, etc.). We propose two types of context awareness based on machine learning: 1) target object recognition and 2) manufacturing information extraction. The target object recognition module tracks information of physical objects located around the user as shown in Figure 4(a). To do this, NFC tag information and visual information taken from the mobile device are used. First, the location information of the manufacturing zone where the user is located is obtained through the NFC tag. Then, the mobile device is used to acquire an image for the corresponding area. For the acquired image, a feature map is constructed using a CNN-based deep learning (e.g., Faster R-CNN), and the physical object in the image such as machine or equipment is segmented and classified [7]. Furthermore, the manufacturing information extraction module retrieves and extracts appropriate manufacturing information for the situation as shown in Figure 4(b). To this end, the manufacturing information related to the target object obtained through the target object recognition module is used together with the characteristics (role, technical level, etc.) of the user. In order to provide the manufacturing situation aware information for the user, another machine learning method such as auto-encoder (AE) will be used.

The proposed dual reality based visualization can play a complementary role between AR and VR environments to solve the existing constraints by applying AR or VR individually. In particular, it can support users to feel high reality and immersive feeling by configuring dynamic visual layout through context-aware dual reality according to the type of smart and wearable devices. In particular, the user can switch between AR and VR environments depending on the dynamic augmentation or immersive rendering as shown in Figure 5. Note that, in the real manufacturing environment, both hands cannot be always used according to the worker's task. If the tool is held in one hand, only the other hand can be used so that the user cannot interact with the smartphone screen, and thus an alternative interaction method such as hand gesture must be supported in both VR and AR environments.

Figure 6 shows some implementation results of the proposed approach. Some of the main ideas have been implemented to provide smart manufacturing services using AR and VR. These results include VR/AR-based visualization of the machine operation in a smart factory, wearable AR to inspect the facility, and area learning for mobile AR to augment virtual machines and facilities into a physical environment.

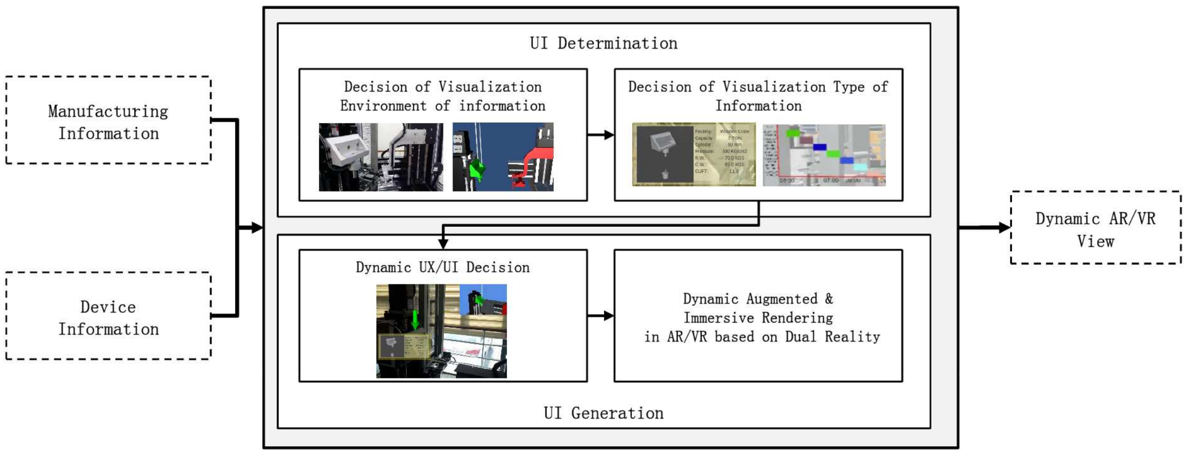

Figure 5. Dual reality

Figure 6. System implementation results

5. **Conclusions.** The paper presented a new and challenging conceptual framework for realizing situation-aware manufacturing UX using dual reality and machining learning-based context awareness. In the physical manufacturing environment, various manufacturing information and user contexts must be simultaneously considered to provide situation-aware visualization, interaction and collaboration methods. The proposed approach analyzes manufacturing contexts through machine learning, and provides user-centric manufacturing UX through AR/VR-based dual reality after classifying and filtering the learned information with respect to user contexts.

Although this research proposes a conceptual but challenging manufacturing UX framework, there are several future research works. We need to implement more application scenarios and test them to evaluate the performance and effectiveness in terms of various aspects of manufacturing UX. In addition, we need to collect more relevant manufacturing data to train the machining learning method and apply the trained machining learning method to the developed applications. Finally, we need qualitative and quantitative evaluation of the developed applications.

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