Designing a Fatigue Monitoring Sensor System with Industry 5.0 principles

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Abstract – **In the Industry 4.0 era, the focus has been on replacing human operators with industrial robots to reduce labors costs. However, it has led to various social and environmental challenges. Industry 5.0 aims to enhance human-robot collaboration (HRC) in intelligent manufacturing environments, promoting both efficiency and flexibility while prioritizing human operators' health and well-being. This study reconfigures a new HRC systems, optimizes layout, and introduces a new Internet of Things (IoT) structure to monitor human-centric manufacturing processes. By utilizing medical-grade sensors for real-time collection of physiological data, the system ensures privacy compliance. The collected data are input into a artificial intelligence algorithm to achieve two main objectives: evaluating operator's health levels and identifying the most efficient movement patterns during the manufacturing process. This research has significant implications for enhancing operator health and well-being in industrial settings.**

Keywords: Industry 5.0, Wearable Sensor, Human well-being, Internet of Thing.

I. INTRODUCTION

A. Research Background

The fourth industrial revolution (Industry 4.0) has greatly transformed manufacturing systems through the integration of cyber-physical systems(CPS), Internet of Things (IoT), and advanced automation. By enabling smart factories, real-time data exchange, and decentralized decision-making, Industry 4.0 has significantly enhanced productivity, flexibility, and operational efficiency across industries. However, as the complexity of manufacturing systems increases and societal expectations evolve, the extreme pursuit of production efficiency by Industry 4.0 has promoted the digital transformation of the manufacturing industry, but has also caused a profound humanistic crisis. The emphasis on automation and technological optimization, while economically beneficial, often overlooks critical aspects such as human well-being, environmental sustainability, and the need for individualized products. The technology-first development model alienates workers into accessories of the production system.

Current research evidence shown that the industrial model of Industry 4.0 has exacerbated social inequality and structural unemployment[7][8][14]. Employment opportunities have been greatly reduced[9], and changes in the labor market have led to a shortage of skilled personnel[10]. New skills and training requirements are needed[12][13], and in the 2030 year disappearance of 800 million jobs is expected to occur[11].

These challenges and crisis underscore a systemic dilemma-whether the single-minded pursuit of hyper-efficiency can be justified without accounting for broader human and ecological considerations. This systemic dilemma directly gave rise to the human centric turn of Industry 5.0. With the continuous growth in industrial production demands, ensuring the well-being of human operators and environmental sustainability has become imperative. Unlike its predecessor, places the human operator at the core of manufacturing systems, promoting collaboration between humans and intelligent machines, where technological advancement serves human needs rather than displacing human agency [1].

B. Research Objective

This study aims to develop an innovative digital framework employing wearable devices, real-time data monitoring, and artificial intelligence to enhance operator safety and human well-being in manufacturing environments. The primary objectives include real-time monitoring of physiological states (e.g., fatigue, stress, musculoskeletal risks), providing immediate alerts and corrective measures, and utilizing AI algorithms to predict potential hazards-combining short-term interventions with long-term optimizations (e.g., workstation redesign, task allocation adjustments) to mitigate occupational risks. Additionally, the research focuses on designing a low-power, modular, and easily deployable IoT system, ensuring wearability and durability while maintaining energy efficiency and wireless connectivity. By validating data accuracy and testing system reliability in real-world manufacturing settings, the
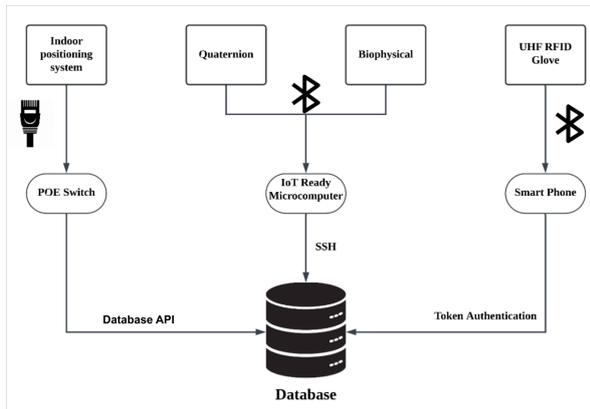
Fig. 1. Fusion Data Acquisition Architecture

Fig. 2. Deployment of a Sensor Fusion System

Table 1. Sensor Location & Function

Sensor	Position	Detection
IPS	Forearm	Movement
Quaternion-1	Dominant Forearm	Activity
Quaternion-2	Non-dominant Forearm	Activity
Quaternion-3	Waist	Posture
EMG1	Dominant-Forearm	Strength
EMG2	Shoulder	Strength
EMG3	Waist	Strength
ECG	Chest	Heart Rate
UHF-RFID Scanner	Dominant-hand	Tool usage

ultimate goal is to establish a scalable, adaptable digital safety-enhancing solution that improves productivity and safeguards operator well-being.

II. METHODOLOGY

A. Data-Collection Architecture

Our study proposes an IoT-based multi-modal data acquisition architecture that integrates indoor positioning, inertial measurement, biophysical signals, and ultra-high frequency radio frequency identification (UHF-RFID) technology. The system architecture incorporates multiple data sources, which transmit data to IoT ready Microcomputer via database API, Bluetooth, and secure communication protocols (SSH, Token Authentication) being stored in a database for further analysis and applications. The overall architecture is shown in Fig 1.

Future research work will focus on optimize data fusion algorithms and enhancing system adaptability in complex environments.

B. Wearable Sensor Architecture

In this section, we show the sensor deployment locations, including the rationale their placement. Special attention will be given to the interplay between sensor positioning and physiological motion patterns, ensuring that the collected data accurately represents the intended actions, and ensuring ergonomic feasibility. See Fig 2 for sensor location deployment. The details of the sensors we deployed are shown in the following Table 1.

C. Fatigue level declaration

In the fatigue declaration part, we did not use the traditional Borg-Scale [18] [17] [19] or self-report questionnaire. We innovatively used a new method. An innovative approach was employed to assess operator fatigue by utilizing a UHF-RFID glove scanner for real-time fatigue
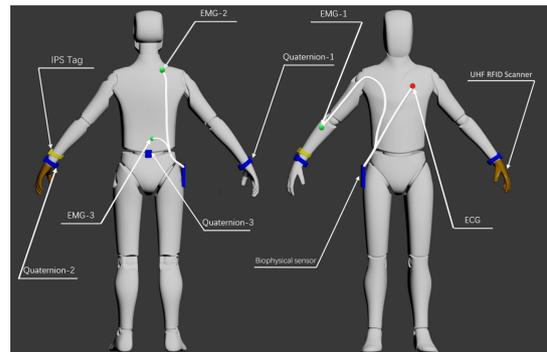
vote declaration. During work periods, operators briefly interacted with different fatigue-level tags using the glove scanner to record their perceived fatigue. The fatigue vote was categorized into five levels, ranging from 1 (slightly tired) to 5 (very tired), different fatigue level have different Electronic Product Code (EPC) value.

During our data collection process, the workers were continuously engaged in the entire spectrum of assembly work at their workstations without interruption. There were no instances where a worker alternated between being fatigued for five minutes and then not fatigued for the next five minutes. Given this sustained activity, we did not set any declarations of "not tired" or "energetic" levels, as the level of fatigue was considered to accumulate progressively over time-only diminishing when the workers took breaks.

Unlike traditional methods such as questionnaires or the Borg scale, which rely on retrospective self-reporting and introduce lag in data collection, this fatigue declaration system enables fatigue simultaneously logging without requiring manual input or stop working. Fatigue declaration system display diagram is shown below Fig 3.

D. Privacy friendly Consideration

Due to this Multi-sensor database storing highly privacy personal data, such as medical/health-related, positional information, etc. The data collection system adopts

Fig. 3. Mock-up of a fatigue declaration system (AI-generated)

an anonymized approach, retaining only identifiers (e.g., 1, 2, 3...) corresponding to the data to ensure that personal identity information cannot be traced. To safeguard the network security of the data collection system, we utilize nProbe to monitor and analyze the upstream and downstream communication traffic related to the database, identifying abnormal behaviors. nProbe can output Net-Flow/IPFIX data and, when integrated with visualization platforms such as ntopng, enables continuous tracking and analysis of the data transmission process.

III. CONTRIBUTION

The contributions of this research are outlined here, with a focus on the innovative aspects explored in detail.

1. We utilize a privacy-friendly system of wearable sensors; unlike traditional computer vision technology, we use wearable sensors to monitor the operator's bio-signals, movement patterns, and positional change data. This approach avoids the privacy issues that may arise from deploying computer vision systems because there is no need to capture or track the operator's facial or body images. Operators can be monitored without worrying about personal privacy leaks, which improves the overall acceptability and reliability of the system.

2. Innovatively created a joint fatigue database of bio-signals and behavioral patterns, by fusing electromyography (EMG), electrocardiography (ECG) data, real time locating system (RTLS) data, and the quaternion data from the operator's real-time movement patterns (from three Quaternion wireless sensors), we successfully created a multi-modal database. Through utilize this database, machine learning algorithm or deep learning algorithm can not only analyse the changes in physiological activities of human operators during work, but also identify fatigue manifestations under different movement patterns, thereby improving the accuracy of fatigue assessment.

3. Innovatively utilizing a UHF-RFID glove scanner, we can track the specific tools used by operators in real

time and correlate these data with physiological metrics for analysis. Prior to deploying the UHF-RFID gloves, we labelled all tools with passive tags that operators might use during their work processes. The subjects do not need to deliberately interact with the tools to accurately identify the passive tags during their tasks. And can collect the strength of RSSI value. Received signal strength indicator (RSSI) is an indication of the power level being received by the receiving radio after the antenna and possible cable loss. When an RSSI value is represented in a negative form (e.g. -100), the closer the value is to 0, the stronger the received signal has been. This approach helps in understanding fatigue variations under different tool usage conditions, thereby enabling optimization of tools usage and workflows to mitigate fatigue-related risks.

4. By deploying a real-time positioning system (RTLS), the spatial position changes and movement behaviors of operators can be monitored in real time, and the position change data can be combined with the bio-signal data. By combining the different tasks that need to be completed at different workstations on the actual assembly line, different task from different workstation and the impact of operation scenarios on fatigue levels can be better captured, thereby improving the accuracy of fatigue prediction.

5. An innovative approach was employed to assess operator fatigue by utilizing a UHF-RFID glove scanner for real-time fatigue vote declaration. During work periods, operators briefly interacted with different fatigue-level tags using the glove scanner to record their perceived fatigue. The fatigue vote was categorized into five levels, ranging from 1 (slightly tired) to 5 (very tired). Unlike traditional methods such as questionnaires or the Borg scale, which rely on retrospective self-reporting and introduce lag in data collection, this system enables fatigue simultaneously logging without requiring manual input.

IV. RESULTS

A. Multi-sensor Dataset

This study utilize InfluxDB as data storage, a database designed specifically for time series data, as a time series database (TSDB) to efficiently store, retrieve, and extract time series data generated during the operation of the fusion sensor system. InfluxDB utilize in house built data engine, the Time Structure Merge Tree (TSM Tree), millisecond-range query performance is achievable even for datasets exceeding one million records, it has massive scalability, allows an applications to scale easily to support millions of IoT devices, and perform real-time analysis [16]. In terms of API extension, by utilize Token-based authentication was implemented to establish a secure connection between Grafana Dashboard and InfluxDB 2.0, facilitating real-time monitoring of multi-sensor data streams. Fig 4 shows the Grafana dashboard connected to InfluxDB.
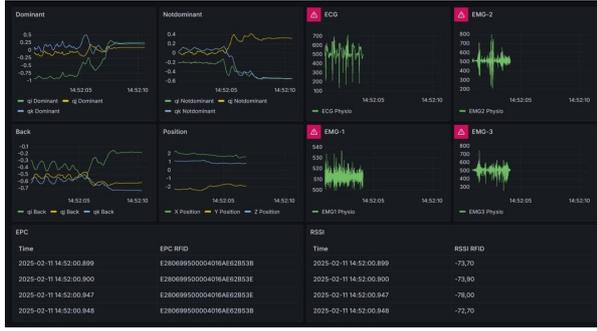
During the fused sensors' data collection process,

Fig. 4. Multi-sensor Grafana Dashboard

Fig. 5. Heatmap of Product Types and Tasks

Grafana receives information from InfluxDB and display the following data:

Data	Unit
Quaternion data from dominant hand.	dimensionless
Quaternion data from not-dominant hand.	dimensionless
Quaternion data from waist.	dimensionless
ECG signal.	mV
EMG-1 (Forearm) signal.	μV
EMG-2 (Shoulder) signal.	μV
EMG-3 (Waist) signal.	μV
EPC value with acquisition timestamp.	unique identifier
RSSI value with acquisition timestamp.	dBm

B. Limitation

The current study has several limitations. First, due to constraints in the industrial deployment site, our participant consisted solely of male operators, lacking data from female operators. Future research will prioritize addressing this gender imbalance. Additionally, hardware-related issues with the UHF-RFID glove scanner had noise in the collected data, complicating subsequent data analysis. Furthermore, occasional positional drift in the indoor positioning system (IPS), caused by uncontrollable factors in the industrial environment, was observed. Future research will address these limitations to validate the framework's broader applicability.

V. CONCLUSIONS

In this study, we innovatively introduced a UHF-RFID glove scanner for tool identification, which to our knowledge has not been previously deployed in real-world industrial settings. By integrating heterogeneous sensors, we successfully developed a novel data fusion framework incorporating spatial positioning data, IMU-derived quaternion streams, physiological sensor inputs ,UHF-RFID tool-detect signals creating the first known multimodal from real industrial activity database of its kind. Demonstrating the feasibility of this framework for real-time, multi-modal data transmission in industrial environments. This achievement lays a solid foundation for sub-
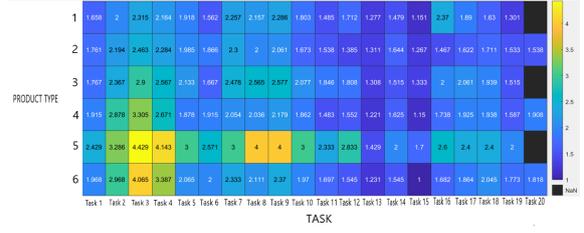
sequent research.

About sensitivity analysis perspective of this research, we involved a statistical analysis focusing on the mean fatigue level across different tasks and product types. As shown in Fig. 5, the heat-map presents the `Mean Fatigue Level` for each activity-product pair, reflecting how different industrial activities impact worker fatigue depending on their operation type.

To evaluate the robustness and stability of the data analysis under varying conditions, we analysis how fatigue levels varied across product type for the same task, and across tasks for the same product type. These variations help to identify the sensitivity of certain activity-product combinations to fatigue-related factors, such as heart effort, muscle load, posture effort, and movement frequency.

Future research will focus on fusion data analysis, data pre-processing, by using artificial intelligence algorithm make prediction on fatigue level of human operator in real industry environment.

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