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Original Article

Real-Time Automated Monitoring of Manual Process Efficiency in Production Line using Camera Vision Systems

Kuhanraj Kandarsamy[3], Amirul Syafiq Sadun[1], Noor Hafizah Sulaiman[1], Muhammad Inam Abbasi[2], Suziana Ahmad[3]

[1]*Faculty of Engineering Technology, Universiti Tun Hussein Onn Malaysia, Pagoh Higher Education Hub, 84600 Pagoh, Muar, Johor, Malaysia*
[2]*Faculty of Electronics and Computer Engineering and Technology (FTKEK), Universiti Teknikal Malaysia Melaka (UTeM), Hang Tuah Jaya, 76100, Melaka, Malaysia.*
[3]*Faculty of Electrical Technology and Engineering (FTKE), Universiti Teknikal Malaysia Melaka (UTeM), Hang Tuah Jaya, 76100, Melaka, Malaysia.*

[1]*Corresponding Author : amirul@uthm.edu.my*

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Abstract - *This research work presents a low-cost camera vision-based system for real-time monitoring of manual production processes. Traditional human inspection techniques are frequently inefficient, inconsistent, and time-consuming, and also possess limited effectiveness in modern manufacturing. To overcome these limitations, a real-time monitoring system is proposed using Python with integrated OpenCV, MediaPipe, and Tkinter based on a graphical interface. The proposed system uses a single RGB webcam to capture marker-less operator motion, trace assembly cycle time, and determine workflow efficiency without the requirement for hardware or wearable sensors. This system can automatically identify production bottlenecks and assess operator performance based on motion patterns, and provide real-time visual feedback to support immediate operator improvement in production efficiency, human error reduction, resource utilization improvement, and process traceability enhancement through data capture. The experimental results show that the proposed method provides high monitoring efficiency exceeding 90% for most test subjects with effective detection out of range occasions and workflow variations. The novelty of this work includes the integration of real-time human motion monitoring, efficiency assessment, and insightful visualization within a simple and affordable framework. Overall, this work establishes the potential of camera vision technology to support practical, accessible, and human-centered monitoring of manual production processes in modern manufacturing systems.*

Keywords - *Camera Vision Technology, Operational Efficiency, Real-Time Monitoring, OpenCV Python, Programming, System GUI.*

1. Introduction

In modern manufacturing, operational efficiency and productivity are important to competitiveness, product quality, and cost control in one production. As production systems become increasingly complex and demand increases, manufacturers face pressure to reduce incompetence, human error, and performance across the production line. Despite advances in automation, a substantial proportion of manufacturing operations, particularly in small- and medium-scale industries, continue to rely heavily on manual assembly and human-based inspection, which are inherently vulnerable to fatigue, subjectivity, and performance variability [1-4]. Previously, for inspection and monitoring in a production line or factory, manual methods such as visual observation, stopwatch cycle time measurement, and process data recording were used. However, by using manual techniques, these methods caused various undesired limitations such as inconsistent accuracy, limited repeatability, delayed feedback, and inability to capture continuous and objective data performances. These limitations have also been discussed in [4], where significant production losses can be caused. In earlier research, it has been revealed that such manual-dependent systems always lead to undetected process nonconformities, inaccurate performance evaluation, and delayed corrective actions, ultimately leading to disturbed production stability and quality. To overcome these limitations, camera vision and computer vision technologies have been expanding discoveries for manufacturing applications, such as detecting defects, motion tracking, and productivity analysis. Vision-based systems present the advantage of contactless measurement, real-time data acquisition, and high repeatability. From the previous research, it is also shown that the usefulness of vision-based measurement for quality control, detection, identification, and cycle time measurement using a camera that is complete with a depth sensor and multi-camera configurations. For example, vision-based systems have also been used for surface detection, monitoring machine conditions, and semi-automated production settings. Conversely, a clear research gap can be identified. Existing vision-based manufacturing reports mainly address fully automated systems, machine center monitoring, and post-processing investigations, which are shown to focus on real-time monitoring of manual compilation production.

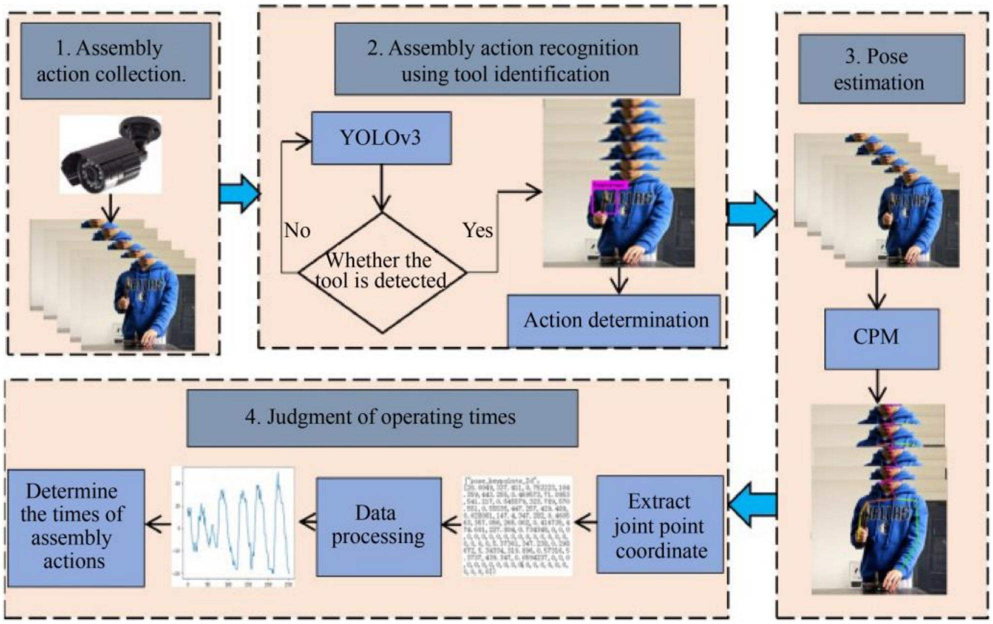

Fig. 1 The process of determining work activities performed by employees [5]

An additional key constraint in previous research is the absence of an integrated, low-cost, and markerless system for continuous monitoring of operator motion, efficiency assessment, and real-time feedback during manual duties. Although some work utilized a motion tracking system and recognition activities, that system required wearable devices and physical markers, which can disturb normal work processes and reduce scalability. Therefore, a practical and accessible solution is required to connect the difference between advanced computer vision methods and real-world monitoring of manual production work [6, 7].

Therefore, to address the limitations, this research presents a camera-based real-time monitoring system for monitoring manual process efficiency in the production manufacturing. The proposed method uses a single low-cost RGB camera with marker-less hand gesture detection based on OpenCv and MediaPipe, which can be used for wearable sensors. By using this system, task completion time, detecting inactivity, and out-of-range movements can be monitored continuously in real-time. In response to these questions, this work proposes a camera vision-based real-time monitoring system exclusively designed for assessing manual process efficiency on the production line. The main contribution of this work is the integration of real-time monitoring, automatic cycle time and efficiency assessment, picturing an alert for inactivity and an interactive graphical interface that provides immediate feedback and performance visualization. Different from previous work that mainly focuses on defect detection or offline productivity analysis, this work highlights human-centered monitoring to support real-time decision-making and fast corrective action during assembly tasks.

The proposed systems are verified by controlled experiments involving multiple operators performing assembly activities. The findings show that the system can capture operator variability, recognize an inefficient work pattern, and objectively compare performance. By presenting a low-cost, simple, and real-time solution, this work provides a practical contribution to camera vision research and addresses an important limitation in manual practice for monitoring. Overall, the work extends the usefulness of camera vision elsewhere in traditional inspection, concerning an integrated and accessible framework for real-time monitoring of manual production processes.

2. Literature Review

Previous existing research related to camera vision systems, manual process monitoring in production, production efficiency investigation, and evaluation in a manufacturing environment is discussed in this part. Additionally, research on vision-based inspection, human motion tracking, and cycle time analysis is presented in this section. By analyzing the previous work, the current limitations can be identified. Based on this review, the research gap addressed by the present study is highlighted.

2.1. Camera Vision in Manufacturing Systems

Computer vision is also called camera vision, which combines software and system engineering to help machines translate and analyze images and video. Its objectives are to duplicate or better human vision using advanced algorithms and machine learning. By its benefit of usable data, camera vision has become an important tool for automation and data-driven decision-making across many industries. Camera vision is widely used in many industries for 3D reconstruction, creating models from 2D images for structural analysis and design checks. By using camera vision, quality inspection can ensure products meet standards; meanwhile, detection uses color, texture, shape, and geometry to detect surface defects. A camera vision system offers improvement of production lines, error reduction, and efficiency. As shown in Figure 2, marker-less visual using camera vision discloses inconsistencies [8].

Fig. 2 Marker-Less visual using camera vision [8]

Camera vision technology extends much more than the detection of defects, as it is an important component for monitoring critical manufacturing parameters such as temperature, speed, and operator performance. It facilitates real-time visual inspection of assembly operations with precise feedback to assist in guiding machines and robots to position, align, and assemble. Motion detection systems track the activity of operators to ensure process consistency, and advanced technology, such as face and eye tracking, assists with vision screening through the monitoring of the movement of the eyes and patterns of gaze to detect visual impairments. These systems screen raw eye-tracking data, carry out statistical analysis, and generate graphical results for extensive assessments.

Camera-based vision technology systems are either marker-based or marker-less. Marker-based systems require physical markers that must be attached to the subject for tracking, whereas marker-less systems use advanced algorithms for detecting and analyzing the motion of the body without additional hardware [10]. Depth-sensing and RGB-D cameras, such as the Microsoft Kinect, add motion analysis through the capture of color and depth information. Artificial intelligence smart cameras, like the Adlink Neon-2000 series, merge image processing with artificial intelligence functions that can work in real time, improving automation, quality checking, and operational effectiveness in production [9]. Machine vision in industrial parameters, such as viewing angle and image resolution, is very important to maintain accuracy so that it can improve efficiency. By proper techniques, quality control, and efficiency in manufacturing can be improved to suit the Industrial 4.0.

2.2. Vision-Based Human Motion and Activity Monitoring

Monitoring systems are essential in the production sector, particularly on production lines, to streamline processes and improve efficiency. Camera vision can be used to perform quality considerations by tracking large thoughts, and can also identify defects and ensure products meet the requirements. By delivering well-timed data, these systems can help manufacturers to overcome appropriate issues quickly, speed up workflows, and enhance means use [11].

Literally, manufacturing can be monitored by manual and automated systems. Manual monitoring changes on operators' visible assessments, data recording, and using simple tools such as data records and a stopwatch. In the meantime, human conclusions can be positive, but they are slow and unpredictable. Automated monitoring commonly uses sensors and camera vision technologies to enable real-time quality control with minimum human involvement. A hybrid system that combines automation and human oversight can be a more complete technique for the production line [12]. An automated system can assemble the real-time data for measuring quality, machine monitoring, early detection, predictive maintenance, and productivity improvements. So in the production, this system can support visual monitoring, cycle time measurement, and feedback to ensure the effectiveness of the production line. Camera-based automated offers are more accurate than traditional methods [13-16].

2.3. Assembly Line Performance Metrics and Cycle Time Analysis

Cycle time, also known as standard time, is the time required to fulfill one full assembly process. Cycle time is a very important indicator of manufacturing performance and is also utilized to evaluate actual production time with the proposed standard time [17].

Cycle time is also important for production planning because it presents the efficient use of manpower, machines, and other resources to achieve the production target. It is also used to construct accurate production programs and timelines to ensure on-time delivery and meet consumer demands [18, 19]. In addition, cycle time supports continuous improvement by indicating performance variations and parts to be improved. It also helps in cost calculations, which include labor and machine usage costs. So the cycle time can be used for performance analysis and future planning in the production line. Overall cycle time is a key measure to improve production, maintenance, and product quality, and also to estimate the time for delivering one product.

Normal Time (TN):

$$TN = TB + TR \quad (1)$$

Where TB is the basic time (time required for the task), and TR is the rest allowance.

Allowances:

$$Allowances = PA + DA + FA \quad (2)$$

Where PA is the personal allowance, DA is the delay allowance, and FA is the fatigue allowance.

Standard Performance Time (SPT):

$$SP = \frac{TN \times 100}{PR} \quad (3)$$

Where PR is the performance rating.

Total Standard Time:

$$Total\ Standard\ Time = TN + Allowances \quad (4)$$

Where TN was mentioned in Equation (1).

Cycle Time:

$$Cycle\ Time = \frac{Total\ Production\ Time}{Number\ of\ Units\ Produced} \quad (5)$$

Takt time is a significant lean manufacturing term used to compute the production rates and align them with customer requirements. It refers to the average duration between the end of one unit's production and the next. Takt refers to the duration to make a cycle across an assembly line and is calculated by dividing the allotted production time within a given timeframe by the amount of work to be produced. [19] describes how to calculate assembly line takt time, process takt time, and process load for a tomato cake production line. It also presents ways of balancing the assembly line by grouping processes and minimizing bottlenecks.

$$Takt\ Time = \frac{Available\ Operating\ Time\ (\frac{sec}{day})}{Daily\ Demand\ (\frac{pieces}{day})} \quad (6)$$

or

$$Takt\ Time = \frac{Available\ Time}{Customer\ Demand} \quad (7)$$

Manufacturing efficiency and productivity can be improved by various methods such as experimentation, optimization, simulation, monitoring, and automation [20]. For precision in productivity and efficiency, these parameters may be calculated by applying formulas available for the purpose. Productivity is a measure of units or components produced within a specific timeframe and is calculated by merely dividing total output by the period taken. Efficiency, on the other hand, compares how well an operator utilizes resources such as time, material, and energy. Efficiency is realized by dividing the actual output by the maximum potential output, which gives us information about the manufacturing process's effectiveness. To put it succinctly, productivity quantifies the amount of output, while efficiency quantifies the quality of use of resources. The productivity and efficiency equation is as follows:

$$Productivity = \frac{Total\ Output}{Time} \quad (8)$$

or

$$\boldsymbol{Efficiency} = \frac{\boldsymbol{Actual\ Output}}{\boldsymbol{Maximum\ Potential}} \quad (9)$$

3. Methodology

This study has started an experimental methodology to develop and evaluate a camera vision-based system for monitoring manual process efficiency in a production line. In this work, the system focused on tracking operator hand movement, determining task completion, and detecting idle time during manual production. All investigations have been conducted under fixed conditions to ensure consistent and fair performance comparison.

3.1. Project design

In this project, there are three main components: the camera, processing unit, and user interface. A Logitech C920 Pro HD webcam is mounted on a tripod above the workstation to capture real-time video of the construction process. The camera and workspace are fixed to maintain reliable detection for this project.

The captured video will be transferred via USB to a laptop and will display results in real-time. The system was developed using Python 3.12. OpenCV was used for video capture and image processing, while MediaPipe enabled marker-less hand gesture detection. This approach allows natural operator movement without requiring wearable devices or physical markers. Moreover, Tkinter and Additional Python libraries and Matplotlib are exploited to design the graphical user interface and display performance data.

A Graphical User Interface (GUI) has been developed to provide live video, real-time detection results, and data performance. The interface displays key data such as the number of completed tasks, efficiency, and inactivity duration. Performance data can also be saved automatically to Microsoft Excel for detailed analysis.

Experimental Setup: A 3D design layout of the project in an assembly line can be observed in Figure 3. Before the experiment was carried out, users set the standard task time and target values. Once the system has been activated, the systems continuously track hand movements within a defined area. Task time and count are recorded inactivity and display a warning message. This real-time alert helps minimize idle time and improve work efficiency. Operator performances are evaluated using cycle time, efficiency, and inactivity data. Cycle time is calculated as the average time required to complete one task, while efficiency is calculated by comparing actual time with the standard time. In this work, the systems have been verified by four volunteers performing the same manual assembly tasks under identical conditions. Based on the results, it can be used for system reliability, detection accuracy, and the difference in operator performance. Overall, the proposed system provides a significantly low-cost and real time solution for monitoring manual assembly efficiency using camera-based vision.

Fig. 3 Experimental Setup; 3D design layout of the project in assembly line

3.2. System block diagram

Figure 4 shows the block diagram of the proposed system, which consists of three main parts. The first part is processing and software, on which A logitech C920 Pro HD webcam is mounted on a tripod to capture real-time video of the assembly process. The video is sent to a laptop via a USB connection. The Laptop works as the processing unit and runs Python 3.12 using PyCharm. It connects the hardware and software systems. The software part includes a GUI that controls the webcam, collects data, and displays operator performance in real time. The GUI can also make the work easier, where performance data can be easily exported to Microsoft Excel for further analysis. The proposed system helps improve production monitoring, reduce inefficiencies, and support efficient quality control in the manufacturing process.

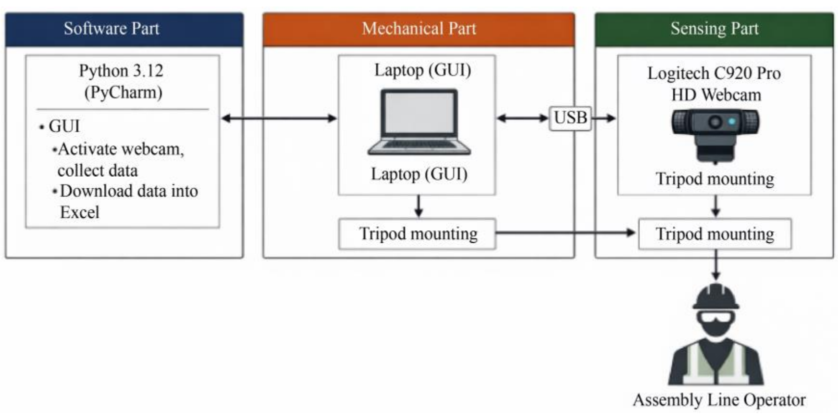

Fig. 4 System Block Diagram

3.3. The Dashboard/Graphical User Interface (GUI)

Graphical User Interface (GUI) has been carried out using Python (PyCharm 3.12) and includes OpenCV, MediaPipe, Matplotlib, Tkinter, and Datetime for live detection of hand gestures. The interface features a live video stream with position markers, a data logging table, and a detection plot. The main performance indicators-out-of-range count, out-of-range time, efficiency rate, and finish count- are displayed along the bottom. Six control buttons (Start, Stop, Reset, Show Data, Show Graph, and Set Standard) facilitate system operation. Figure 5 shows the GUI design aimed at facilitating monitoring and improving workflow effectiveness.

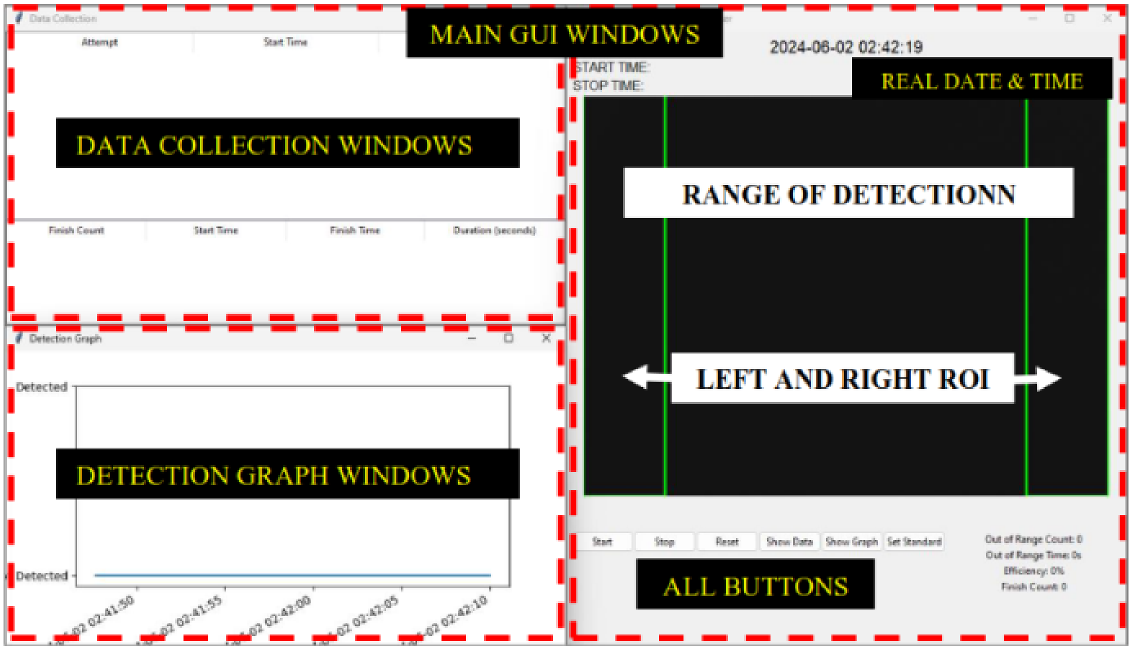

Fig. 5 System Block Diagram

4. Results and Discussion

This part summarizes the results of system function testing, hand gesture recognition rate, system alertness, and operator effectiveness.

From the results, the data has been analyzed to evaluate the system performance with particular focus on the count of products completed, average time consumed in completing tasks, level of efficiency, and number of unnoticed hand movements.

4.1. System Functionality Test and Detection Performance

The first stage of evaluation focused on verifying the functionality of the proposed camera vision-based monitoring system under controlled experimental conditions.

The system was tested with four volunteers performing manual assembly tasks using Lego components, representing a simplified but repeatable production scenario. Each participant was required to assemble five units within a fixed time window while the system continuously monitored hand movements, task completion time, and inactivity duration.

The proposed system functional test was performed to ascertain the general capability of the vision-based system. The capacity of the system to properly detect and record the manufacturing process was estimated using numerous test runs. All the tests were designed to mimic actual production conditions, ensuring that the output will be indicative of hand detection and the true functioning competence of 4 volunteers. Each volunteer must construct 5 Lego Bricks using Lego within 30 seconds.

Aside from that, hand motion recognition is a significant feature of the system to enable operator movement observation and precise data collection. Detection accuracy was validated via comparison between detected gestures and true gestures performed by the operators.

Figure 6 illustrates the test scenario that combines camera detection and data harvesting. Besides, Figure 7 shows the testing results, wherein it can be realized that the slower the process, the longer the time required to complete the task.

This is evident in Volunteer 4, wherein frequent breaks leave it with a significantly higher completion time of 6.47 seconds compared to Volunteers 1 and 2, who worked much faster with minimal breaks. The form shows that numerous stops during the task increase the overall process time, affecting output and efficiency in the production line.

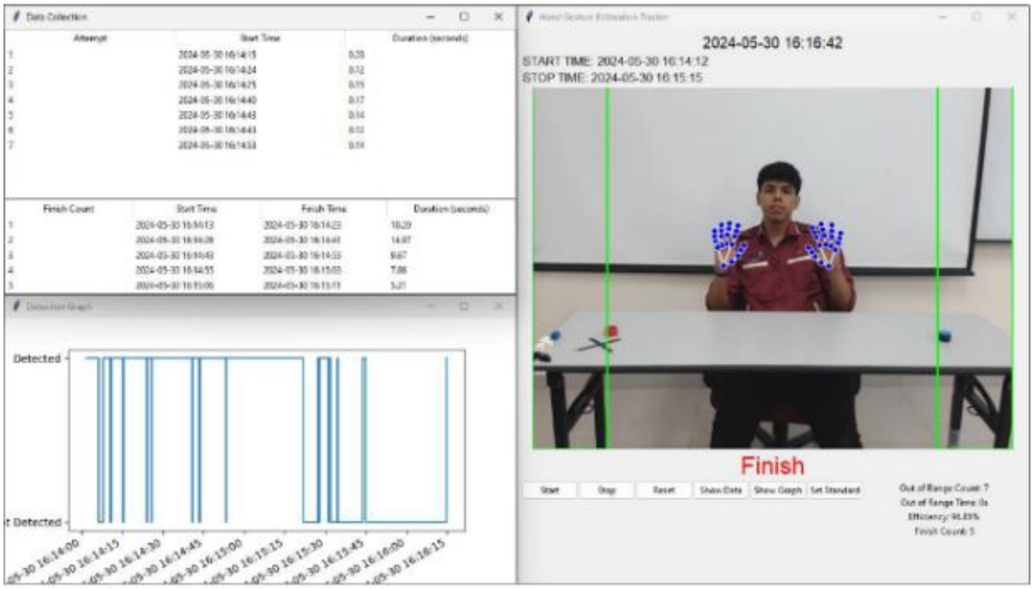

Fig. 6 System Functionality Test

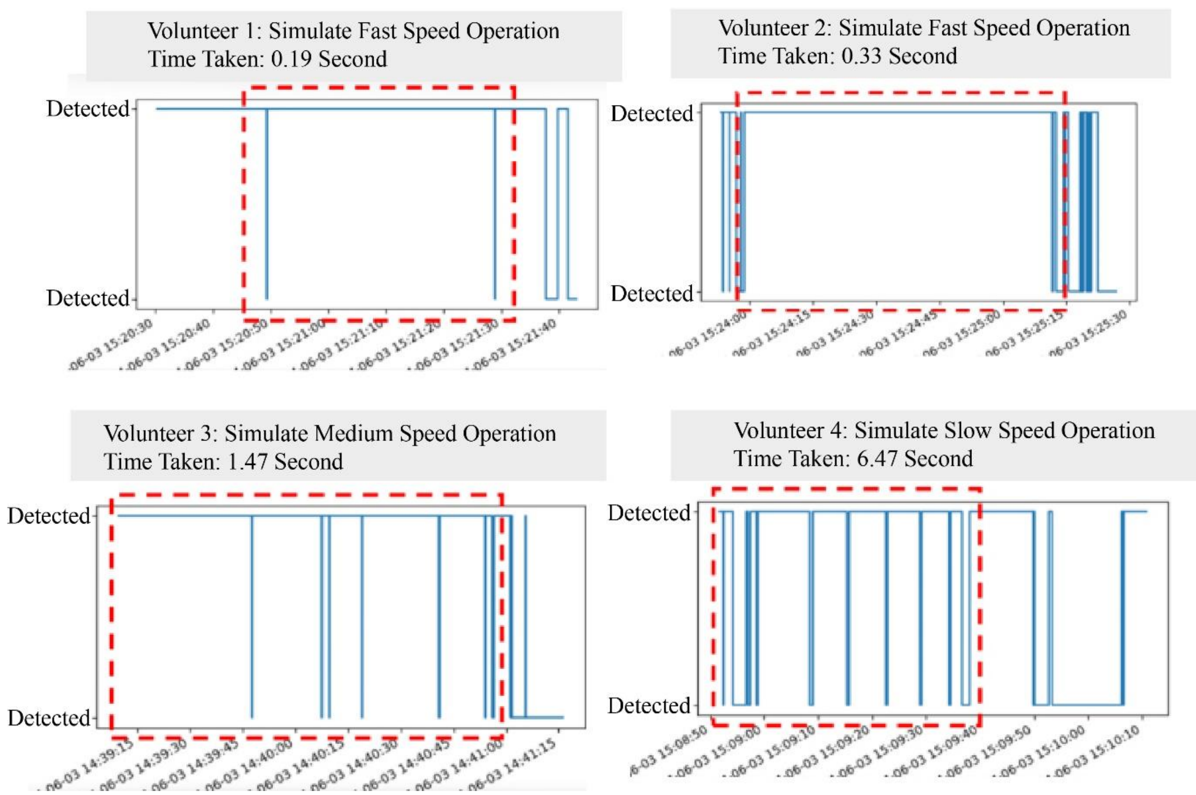

Fig. 7 System Functionality Test Results for (a) Volunteer 1, (b) Volunteer 2, (c) Volunteer 3, and (d) Volunteer 4

4.2. Operator Performance Comparison

Table 1 provides a summary of the performance taken for the four volunteers, which includes average task accomplishment time, number of out-of-range recognitions, collective idle time, and estimated productivity. As depicted in Table 1, the efficiency results show that the proposed system executes consistently for 4 volunteers in this investigation. As can be seen, Volunteers 1 to 3 are achieving high efficiency values above 90%, which can indicate stable operation and a minimum range. Volunteer 1 showed the highest efficiency, presenting consistent system tracking throughout the task duration. Difference with the Volunteer 4 showed a lower efficiency of 59.25%, which is credited to the frequency of range events during the trial in this experimental work. To ensure expressive assessment and verify the performance values, efficiency for this case has also been calculated using manual methods. Overall, the results show that the systems maintain high efficiency under normal conditions while emphasizing the need for future strength improvement with excessive out-of-range behavior. From the collected data, it can be seen that transparent contrasts in operator behavior and performance have been observed, particularly emphasizing the system's ability to distinguish productivity levels objectively.

Table 1. Summary of results

Volunteer	Average Time (s)	Out of Range Time (s)	Efficiency (%)
1	10.06	0.19	98.11
2	10.17	0.33	96.76
3	14.99	1.47	90.19
4	05.28	6.47	59.25

4.3. Inactivity Detection and Alert Effectiveness

A key feature of the proposed system is its ability to detect prolonged inactivity and provide real-time alerts. During the experiments, the system successfully identified periods when hand movements were not detected within the predefined time threshold. When inactivity exceeded 60 seconds, a warning alert was displayed prominently on the Graphical User Interface.

The alert mechanism proved effective in signaling potential workflow issues such as operator distraction, hand movement outside the detection area, or temporary task interruption. This functionality is particularly valuable in real production environments, where immediate feedback can reduce idle time and support continuous operator engagement. Compared to conventional manual observation, the automated alert system offers faster and more objective detection of inefficiencies.

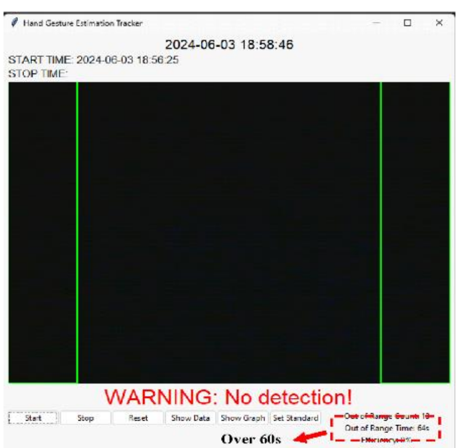

Fig. 8 Main GUI window showing warning alert pop-up

The system alert feature plays a critical role in the manual process efficiency monitoring framework that issues immediate alerts when operator hand movements are not detected within the defined interval. As shown in Figure 8, the warning appears prominently at the center of the main GUI for easy visibility. If no hand gestures are detected for 60 consecutive seconds, the system triggers a "WARNING: No detection!" alert, indicating that the operator may be out of range or their gestures are not being recognized. The alert prompts the operator to re-enter the designated area or modify hand gestures to ensure accurate detection. Through the minimization of downtime and continuation of operator engagement, this function assists in operational efficiency and facilitates timely remedial measures, thus being extremely beneficial in environments needing constant monitoring.

4.4. Visualization and Data Interpretation

The graphical performance dashboard can be user-friendly because it is easy to understand the results. From the display, it can be observed that the real-time data and numbers make fast observation of performance trends and help to recognize bottlenecks or unexpected patterns. This system also has advantages by providing an option to export data to Microsoft Excel with detailed analysis and long-term tracking performances.

4.5. Discussion of System Effectiveness and Limitations

Overall, the experimental results demonstrate that the proposed camera vision-based monitoring system is effective in capturing operator performance variations, identifying workflow inefficiencies, and providing real-time feedback. The use of a single low-cost RGB camera and marker-less detection significantly reduces system complexity and deployment cost compared to multi-camera or sensor-based solutions reported in previous studies. However, several limitations were observed. Detection performance can be influenced by lighting conditions, camera placement, and hand occlusion. Additionally, efficiency values exceeding 100% indicate that predefined standard times must be carefully selected to reflect realistic production benchmarks. These factors should be addressed in future work through improved calibration, adaptive thresholds, and enhanced lighting control

5. Conclusions

This research shows a camera vision-based approach for real-time monitoring of manual process efficiency in the manufacturing sector. The proposed systems can be useful to track operator hand movements, determine task completion time, detect idle time, and evaluate efficiency using a low-cost

RGB camera and marker-less vision technology. Based on experimental works, it can be shown that the system can differentiate in operator performance, identify workflow disturbances, and provide immediate visual feedback through a user interface. From the results, it can be validated that the proposed method provides practical, scalable, and cost-effective solutions for manual production processes and presents strong potential to be commercially viable in manufacturing sectors.

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