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Applying a Fusion of Wearable Sensors and a Cognitive Inspired Architecture to Real-time Ergonomics Analysis of Manual Assembly Tasks

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Abstract:
High value manufacturing systems still require ergonomically intensive manual activities. Examples include the aerospace industry where the fitting of pipes and wiring into confined spaces in aircraft wings is still a manual operation. In these environments, workers are subjected to ergonomically awkward forces and postures for long periods of time. This leads to musculoskeletal injuries that severely limit the output of a shopfloor leading to loss of productivity. The use of tools such as wearable sensors could provide a way to track the ergonomics of workers in real time. However, an information processing architecture is required in order to ensure that data is processed in real time and in a manner that meaningful action points are retrieved for use by workers.
In this work, based on the Adaptive Control of Thought—Rational (ACT-R) cognitive framework, we propose a Cognitive Architecture for Wearable Sensors (CAWES); a wearable sensor system and cognitive architecture that is capable of taking data streams from multiple wearable sensors on a worker's body and fusing them to enable digitisation, tracking and analysis of human ergonomics in real time on a shopfloor. Furthermore, through tactile feedback, the architecture is able to inform workers in real time when ergonomics rules are broken. The architecture is validated through the use of an aerospace case study undertaken in laboratory conditions. The results from the validation are encouraging and in the future, further tests will be performed in an actual working environment.

Keywords: real-time, ergonomics, manual assembly, wearable

1.0 Introduction
High value manufacturing systems still require ergonomically intensive manual activities. Examples include the aerospace industry where the fitting of pipes and wiring into confined spaces in aircraft wings is still a manual operation (Figure 1). Such manual activities could benefit from real time digitization in order to alert workers when they exceed ergonomically safe limits [1]. Currently, this is not the case and workers are exposed to dangerous levels of ergonomically awkward positions that lead to musculoskeletal conditions [2][3]. This results in sick days off and impacts the productivity of a shop floor, company and consequently a nation [4].

Figure 1. An aircraft wing assembly process

This is a major concern for a leading Aircraft manufacturer, employing over 6000 workers to produce a thousand Aircraft wings annually. Although common arm and hand activities do not present a significant injury risk in daily life; in the work environment these actions usually need to be repeated with strong forces applied. This leads to work-related musculoskeletal disorders [5]. In general, back and spinal injuries are the most common musculoskeletal injuries, affecting more than a quarter of adults each year. These musculoskeletal injuries are a major cause of disability in work environments with manual activities [6].

For a manufacturing system such as aeroplane assembly, the issue of musculoskeletal injuries severely limits output. For example, in addition to the 20.9 hour part preparation process, a single aircraft wing assembly requires 65.7 hours of manual installation of the pipeline process [7]. Ensuring safe ergonomic standards of workers is an important factor during such manual assembly processes. A worker in such an environment could benefit from a digital real time system that informs them when to take a break and when force limits are exceeded during work. Such a digital real time system could keep track of all the activities worked on during a shift and then recommend other activities to compensate or achieve an ergonomic balance workload profile. Furthermore, such a system will also ensure that shop floor manual activities are recorded for offline analysis and consequently ergonomic improvement of current manual activities. In order to achieve this, real time manual activity digitization through sensors, real time ergonomic assessment, and real time feedback to workers is needed. Towards this, in the next section, we present a review of work that has been carried out towards supporting real time ergonomic assessment of manual activities on shop floors.

2.0 Literature review

The attractiveness of applying sensors to digitize processes in manufacturing has been increasing in recent years. For example, Kerner et al. [8] investigated the use of a wearable sensor placed on a glove for push pull operations during manual assembly. In [8] the authors aimed to provide real-time feedback to workers as a source of automated task completion in a manufacturing process.

Until very recently, ergonomic assessment of manual tasks were often preventative and assessed beforehand. CAD like software such as SAMMIE CAD ltd [9] were often used to derive the necessary ergonomics requirements that would ensure the safety of workers during manual assembly. However, such software did not capture the intricacies that were unforeseen during initial evaluations and studies. Also, it did not provide instant feedback to workers. For real time ergonomic assessment, posture recognition, detection of forces being generated and used by limbs as well as recognition of the weight being carried by workers is needed in real time. In order to achieve real time posture recognition, the acquisition of data for joint angles calculation is required. This requires the need for motion capture technology and there have been multiple research works conducted in this area. For example, OpenPose is an open library and package built by the Perceptual Computing Lab of Carnegie Mellon University (CMU) that detects human body and outputs the acquired human body image as a skeleton image of the human body and the two-dimensional coordinate data of each joint point of the human body. This is achieved through the use of a convolutional network to extract features of the human body. Furthermore, bipartite matching is used to perform part association, and connect the joint points of the same person [10].

A similar technology called Kinect has been used by Prabhu et al. [11] to capture human motion information in conjunction with machine learning algorithms. This was used to analyse the digitisation of skilled workers in composite laying operations. Furthermore, [12][13] discuss how Kinect sensors could be used to ergonomically assess workers on the shop floor in real time and provide feedback to them. However, such devices require line of sight to the worker and have limited field of view. By using more than one Kinect, it is, however, possible to provide multiple viewpoints of workers and ensure that there is adequate coverage of the workspace [14][15].

However, working in confined areas or areas that require the ingress of human limbs as in Figure 1 above, will impact the data collection process. In order to solve this challenge, wearable sensors are currently being explored. For example, a low-cost ubiquitous approach that made use of the built-in sensors in smartphones were used to monitor construction worker's postures and identify potential work-related ergonomic risk in [16][17][18]. Similarly [19] made use of the off-the-shelf single-parameter monitoring wearable sensor (SPMWS), the ActiGraph GT9X Link, which was worn at six locations on the body, and a multi-parameter monitoring wearable sensor (MPMWS), the Zephyr BioHarness™3, to investigate the effect of sensor placement on the trunk posture for construction activities.

However, the data from the wearables needs to be processed and data fusion techniques applied in order to derive meaningful insight about the ergonomic conditions of the workers. Research has investigated the use of various machine learning methodologies such as Support Vector Machines to extract various activities related to lifting, transporting, pushing and pulling [17]; the use of Regression to understand the relationship between each part of the spinal curve and the corresponding upright posture [20], Artificial Neural Networks to evaluate posture [21] and various data fusion techniques such as Kalman filters [22], k-nearest neighbour (kNN) [23], Dempster-Shafer evidence theory [24], amongst others [25].

Unlike these previous works, we propose the use of a cognitive architecture to process and fuse the streams of data collected from wearable sensors on a worker's body [26]. This is because a human is a cognitive agent and in the future wearables will be seen as extensions of the human cognition [27][28][29]. Taking this view will enable closer fusion of both cognitive agents (humans and wearables) together. As a result, in this work, we take the view that the data collected by sensors on the human body should be fused and processed by a cognitive element attached to the body.

Furthermore, the application of a cognitive architecture enables us to model human and environment conditions virtually so that insights can be gained on how to better understand the data generated by the wearables and the conditions under which the data was collected [26]. We believe that by following this approach, a closer integration and fusion of wearables and their corresponding data processing elements will result. In the future, this enables us to develop a cognitive wearable system that could be extended to a wearable robotic system capable of aiding humans during manual activities.

Cognitive architectures have their roots in the robotic community where they were developed in order to achieve autonomous agents that can navigate the real world. ACT-R (Adaptive Control of Thought—Rational) [26] and SOAR are among the established and earliest cognitive architectures still in use today [28]. Furthermore, these are the architectures that have been applied by researchers to achieve closer fusion between the human body and a wearable external asset [29]. As discussed previously, it is proposed that such an external asset should be cognitive in its nature in order to ensure closer and seamless fusion with the human's musculoskeletal system.

All cognitive architectures require a means to perceive their immediate environment. Towards this, use is made of two wearable technologies, Perception Neuron and Myo armband that can be worn, non-intrusively, on the human body. Nevertheless, these two sensor modalities collect different data types from their surrounding environment. As a result, data from these two sensors need to be fused together because each one on its own is not sufficient to discover whether ergonomic rules are being followed or not. The Perception Neuron® is a whole body motion sensing capture system, comprising of a comprehensive set of wearable sensors. It collects data on limb movements. This sensor system has been used for a variety of tasks such as in Kim et al. [30] where the motions of trainee surgeons were examined in order to create a system that helps to optimise body posture for doctors performing operations. When used within a games engine and Virtual Reality Rendering Development environment, Perception Neuron can provide a data stream for real time and near to real-time rendering of human movement [31].

Another wearable sensor for obtaining data streams is an armband based device called Myo. This armband is a sensor that collects Electromyography signals from the forearm and upper arm. From these signals, it is possible to detect arm and hand gestures [32]. Myo has been used by [33] in the realm of physiotherapy in order to assess the effectiveness of treatments and assist with the aim of eventually assisting in the early diagnosis of patient conditions. In research by [34] experiments have been undertaken to investigate Myo in terms of the measurement of fatigue in muscles in order to validate the device as an accepted method for fatigue assessment. Authors such as Silva et al. [35] have also experimented with using Myo in combination with a sensor such as Leap motion (used for fine grain hand movement tracking) in order to overcome the limitations of both sensor types when they are used independently. Finally Koskimäki et al. [36] put forward a data set relating to the capture of gym based fitness movements with the aim of describing more challenging movements for use in the development of more capable machine learning approaches for movement detection and identification.

Faber et al. [37] estimated hand forces by measuring the ground reaction force with the full-body inertial motion capture system through a mechanical sensor mounted on the sole. The core principle of the system is that while an object exerts a different amount of force on the hand, the foot exerts a different amount of force on the ground. Noguera (2018) [7] judged the weight of the pipe taken by the worker's hand by installing pressure sensors at the fingertips of the gloves in conjunction with a machine-learning algorithm. Even though the glove has been mounted on the back of the hand, the six force-sensing resistors installed at the fingertips still affect the activity of the hands, especially when it comes to the need for fine-grained operation.

Another wearable technology is the Kinetic Reflex. It is equipped with an inertial measurement unit (accelerometer and gyroscope) that is worn around the user's waist. When doing daily work in a factory, warehouse, or other location, the device detects high-risk actions by workers, such as lifting an object by bending over rather than bending the knee. When a high-risk condition is detected, it provides a real-time reminder with a slight vibration and a warning message on the screen. Kinetic reflex pays more attention to the back, and it is more suitable for workers who are often carrying heavy objects in logistics companies. However, it is gratifying to note that there are cases where workers have reduced their high-risk posture by 84% after wearing Kinetic reflex for five weeks [38]. This shows that ergonomic reminders do help workers improve their habits.

By using these technologies with support from a “wearable” cognitive architecture, the aim is to fuse the data streams from these sensing modalities towards digitally tracking and analysing the ergonomics of a worker in real time. The wearable cognitive architecture developed in this work was inspired by the Adaptive Control of Thought—Rational (ACT-R) architecture. The ACT-R architecture is a versatile architecture that has been used successfully to create models in domains such as learning and memory, problem solving and decision making, language and communication, perception and attention as well as researching cognitive development. The structure of the architecture offers the ability to add assumptions, in the form of rules, about the domain of interest into the architecture. Compared to the SOAR architecture, the features of ACT-R makes it more cognitively plausible in researching the way human cognition works.

The ACT-R architecture has four main modules and a central production system. Each of the modules have a related buffer. The modules are as follows: (a) a visual module for encoding and representing objects detected in the environment visually, (b) an intentional module for keeping track of goals and intentions of the user, (c) a declarative module for retrieving relevant information from memory, and (d) a manual module for planning motion and activating the limbs. The central production system coordinates the communication and performance of these modules through the application of developed production rules. As discussed above, these production rules can be updated depending on the intricacies of the domain. As a result of this feature, the ACT-R architecture enables us to investigate various production rules to achieve real time ergonomics assessment in this work [26][39].

The third section of this paper introduces this wearable cognitive architecture as well as the wearable sensors used. The fourth section discusses the results of the experiments that were conducted while the fifth section discusses the results obtained as well as limitations of the approach. The concluding section six provides an agenda for future work.

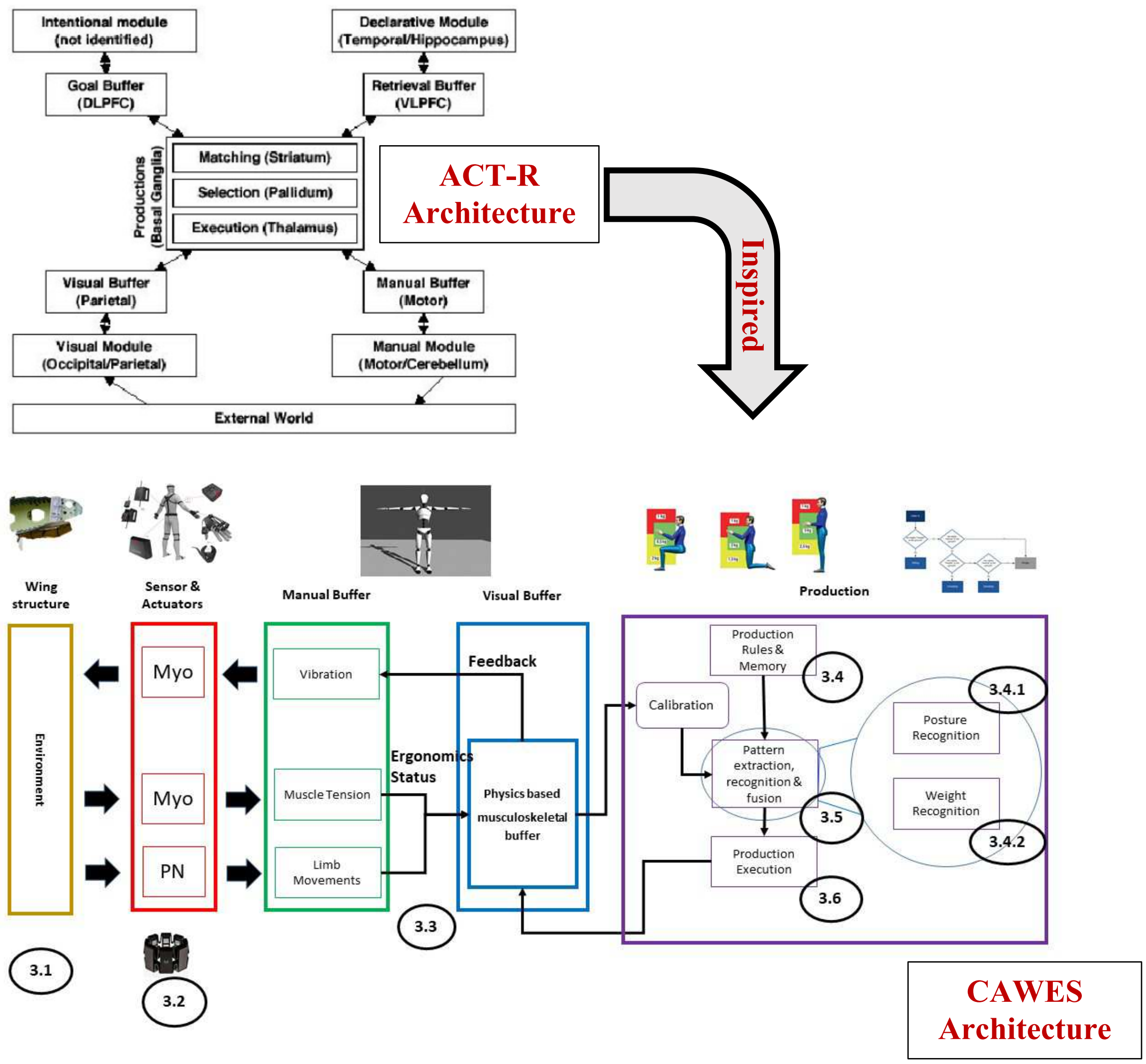


Figure 2. A Cognitive Architecture for Wearable Sensors (CAWES) based on applying the ACT-R architecture [26] to develop a data fusion pipeline for data streams from multiple wearable sensors. The numbers beside each module relate to the corresponding sections that provide relevant detailed narrative.

3.0 Methodology

The aim of this work is to propose and introduce an architecture inspired by the ACT-R cognitive architecture to process and fuse the data obtained from off-the-shelf wearable sensors. This approach will enable the tracking of worker assembly tasks, the development of ergonomic indicators for assembly operations as well as reveal methods to extract these ergonomic indicators from real-time data. The rich data obtained by the wearable motion capture system can be used to do more analysis both online and offline. While the human electromyography signal is complex, we show that production rule heuristics could be developed to extract information from it and fuse it with the Perceptron Neuron data stream. Furthermore, the use of virtual reality technology (via the visual buffer in the cognitive architecture shown in Figure 2) enables the adaption of workers to new assembly processes and the development of standardized and safe operating habits. In this work, tactile feedback via the Myo armband is used to provide feedback to a worker when ergonomic rules are broken.

As mentioned before, there are many cognitive architectures in relevant literature [28]. In this work, focus is given to the development of an architecture, called CAWES (Cognitive Architecture for Wearable Sensors) to fuse data streams from two wearable sensors for the digitisation, tracking and analysis of human ergonomics in real time. The CAWES architecture shown in Figure 2 is inspired by the ACT-R architecture and is detailed in the following sub-sections.

3.1 Environment: In the current work, the environment is comprised of participants carrying out tasks related to carrying weights and adopting various postures that could be adopted by workers during their work. These postures and the recommended weights for each of them is defined in Figure 3. As will be seen in Figure 3, these recommendations could be quite challenging to remember for a worker on a shopfloor especially when operating in the environment depicted in Figure 1.

Task duration	0–8 h	
Frequency	0,2 – 12 lifts/min	
Action time	≤ 3 s	> 3 s
Posture	Recommended mass limit	
	5 kg	2 kg
	2.5 kg	1 kg
	1 kg	0.5 kg
	2 kg	1 kg
	1.5 kg	0.5 kg
	1 kg	0.5 kg
	4.5 kg	2 kg
	2 kg	1 kg
	1 kg	0.5 kg

Figure 3. Various postures and allowable weights

3.2 Sensors and actuators: A Perception Neuron® was used obtain joint data from a worker while EMG data was obtained from a Myo armband. After posture recognition and weight recognition (discussed below), the corresponding outputs were fused using the ergonomic rules developed from Figure 3. The worker is made aware of the cognitive architecture's decision via the Myo armband tactile vibrations. If the worker is outside the ergonomic recommendations, the system feedbacks to the worker through vibrations in the Myo armband. Consequently, the Myo armband serves two purposes: to track the worker's EMG signal during activities and to feedback to the worker. Such a system ensures that feedback is provided to the worker non-intrusively.

3.3 Manual, Visual and Physics based Musculoskeletal buffer: The physics based module in the architecture, proposed in Figure 2, was used as humans have a heuristic model of how physics affects objects' motions and behaviour as developed through interactions with various objects. These physics models enable humans to perform internal simulations on how to dunk a ball into a hoop for example by running multiple hypothesis on the correct muscle tensions and motor controls to convert the internal simulation into physical muscle and motor kinematics. In this work, we make use of the Unity environment that comes with the Perceptron Neuron software to support the construction of the physics based musculoskeletal buffer. The mannequin in Figure 4 was used as a one to one mapping of the various joints in the human body and hence offered the capability to track the human body in real time. In this work, the manual buffer was used to acquire data from wearable sensors used as well as configure vibration data feedback to workers.

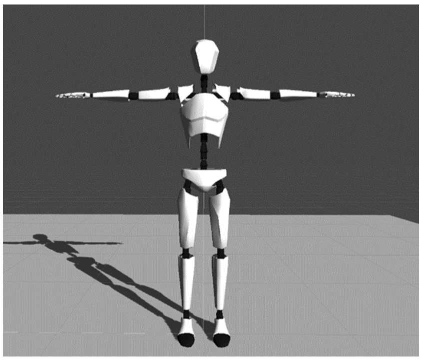


Figure 4. The mannequin

3.4 Production Rules and Memory*:* As presented in Figure 3, the aerospace company's ergonomics document describes the possible postures that arise during shopfloor work together with the weights that are ergonomically safe to hold with such postures. As would be seen, there is information on frequency of weights at various postures that could be lifted per minute as well as how long each posture can be held for. This information were digitised into production rules for the production memory module of the CAWES architecture.

According to the leading aerospace manufacturer's ergonomics booklet, the recommended mass limits are different when the body is in different postures or when the length of action time is different. Therefore, the system needs to recognise the posture state of the human body and recognise the weight of the object in the hands. In addition, the goal for the system was to implement a real-time ergonomic analysis system, so the two recognition systems should be fused together for better understanding of a worker's posture. The two recognition systems required will now be discussed.

3.4.1 Posture recognition: The nine poses in the manual are a combination of lower body states and upper body states. As shown in Figure 5 the lower body state can be divided into three states: standing, kneeling and sitting. While the upper body state can be divided into three states: "red state", "green state" and "yellow state".

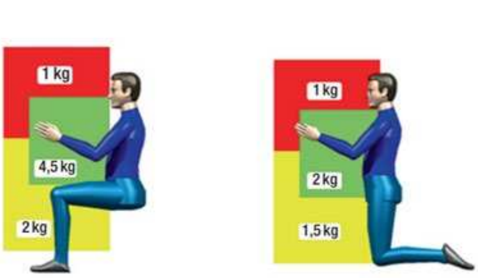


Figure 5. Simplified recommended mass limits and zones for repetitive tasks [40]

The "red state" corresponds to the state of the human body when the human body needs the spine to stand straight, and the arms are lifted to reach the red area. The "green state" corresponds to the human body state in which the human body keeps the spine straight, and the arms remain in an approximately horizontal state. The "yellow state" corresponds to the human spine bent and the arms tilted down so that the hands can reach the yellow area.

3.4.1.1 Lower body state recognition: When considering the recognition of these postures, the ground is used as a reference point. There are several ways to distinguish between the states of standing, kneeling and sitting. Two methods are proposed in this work. **The first method** made use of the height of the joints relative to the ground plane while **the second method** made use of the joint angles.

In the first method, the height of the femur bone (thigh bone) relative to the ground and the height of the lower leg (tibia) relative to the ground were used to determine the state of the lower body. This involved using the values of the height of the hip joint, knee joint and ankle joint when the robot model in Unity is upright. The height values of these joints correspond to the Y-axis value in the world coordinate system of Unity and their values are shown in Table 1. From these values, it was possible to obtain the leg and thigh bone lengths.

Table 1. Height of three joints when the robot model in Unity is upright. It should be noted that the values of the three joints would vary across ethnical backgrounds. In this work, these values were informed by the participants' body morphology.

	Hips joint	Knee	Ankle
Y of position	1.114	0.569	0.102

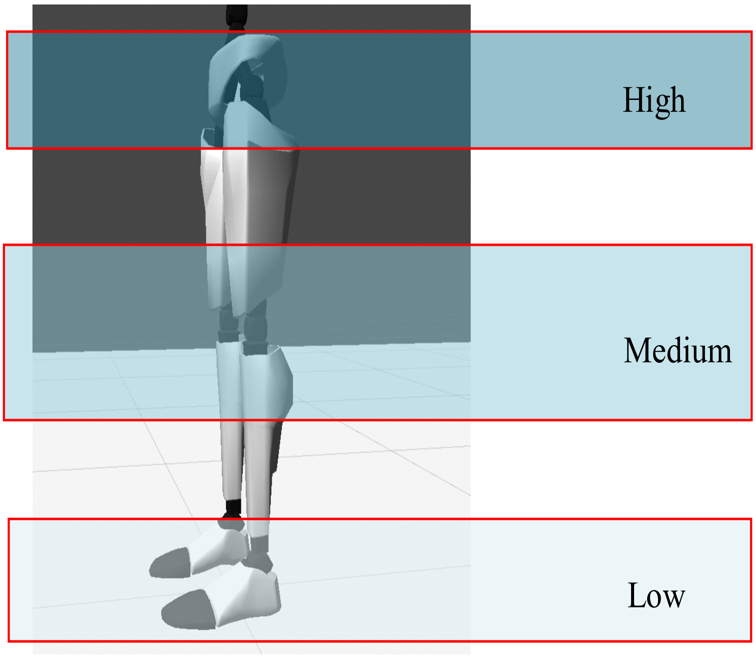


Figure 6. Joint height level partitioning diagram

The three height values were then used to inform three range values of "High", "Medium" and "Low", as shown in Figure 6. This is because each joint is not a fixed value when the human body performs various postures in reality and also because of the differences in the joint values in the human population. The ranges are shown in Table 2. The height of the hip joint plus one-fifth of the length of the thigh are set to the upper limit of the "High" range and the height of the hip joint minus one-quarter of the thigh is set to " The lower bound of the High" range.

The ankle height plus one-fifth of the leg length was used as the upper limit of the "Low" range and 0 was used for the lower limit of the "Low" range. Since the sitting position is largely influenced by the height of the chair, the range of the "Medium" level was determined to be wider than the range of the first two height levels. We set the height of the knee when standing upright plus one-third of the length of the thigh to the upper limit of the "Medium" range and the height of the knee when standing upright minus one-third of the length of the lower leg to the lower limit of the "Medium" range.

Table 2. The height range values of the hip, knee and ankle joints

	High	Medium	Low
Interval range	0.9775 - 1.223	0.413 - 0.751	0 – 0.195

Table 3. Method 1 Rule Table. The relationships between the joints and the range values the joints fall in during manual work are used to determine the lower body state status. For example, when the hip joint is in the high range and the knee joint is in the medium range, then a participant is estimated to be standing.

Joint height level		Lower body state
Hips joint	Knee	
High	Medium	Standing
Medium	Medium	Sitting
Medium	Low	Kneeling

After determining the interval of each height level, the posture of the lower body can be estimated according to the height of the hip and knee joints from the floor as shown in Table 3. If the hip joint is in the "High" range, we infer that the worker is in a "Standing" state. If the position of the knee is in the "Low" range, we infer that the worker is in a "Kneeling" state. If both joints are at "Medium" level, we infer that the worker is in a "Sitting" state. If none of the three states is satisfied, the system does nothing.

The second method distinguishes the state of the lower body by determining the angle between the thigh and the ground and the angle between the lower leg and the ground. When a person is standing, the thighs and calves can be seen as almost perpendicular to the ground. When a person is kneeling, the calf is parallel to the ground, and the thigh is perpendicular to the ground. When a person is sitting, the calf is perpendicular to the ground, and the thigh is parallel to the ground.

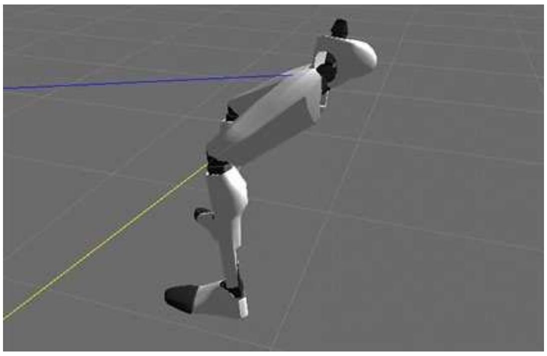


Figure 7. The angle between the left thigh and the horizontal plane when the person is sitting

However, the terms "vertical" and "parallel" as used herein are ideal. It is impossible to achieve true vertical and parallel. Especially when the person is in the "sitting" state, the angle between the thigh and the ground is largely affected by the length of the calf and the height of the chair. As shown in Figure 7, the angle between the thigh and the ground is 35.9265°. Therefore, the range of angle requirements for the identification of each state is also broadened, as shown in Table 4.

Table 4. Parallel and vertical definitions in the system

	"Parallel" (degree)	"Vertical" (degree)
Interval range	0 - 45	60 - 90

Another consideration is that since the person is sitting, the calves are in a relaxed state. Among the states of "standing", "kneeling" and "sitting", people's thighs are "parallel" to the ground only in the state of "sitting". Therefore, the identification of the state of "sitting" only considers whether the angle between the thighs and the horizontal plane is "parallel" or not. The specific identification system is shown in Figure 8.

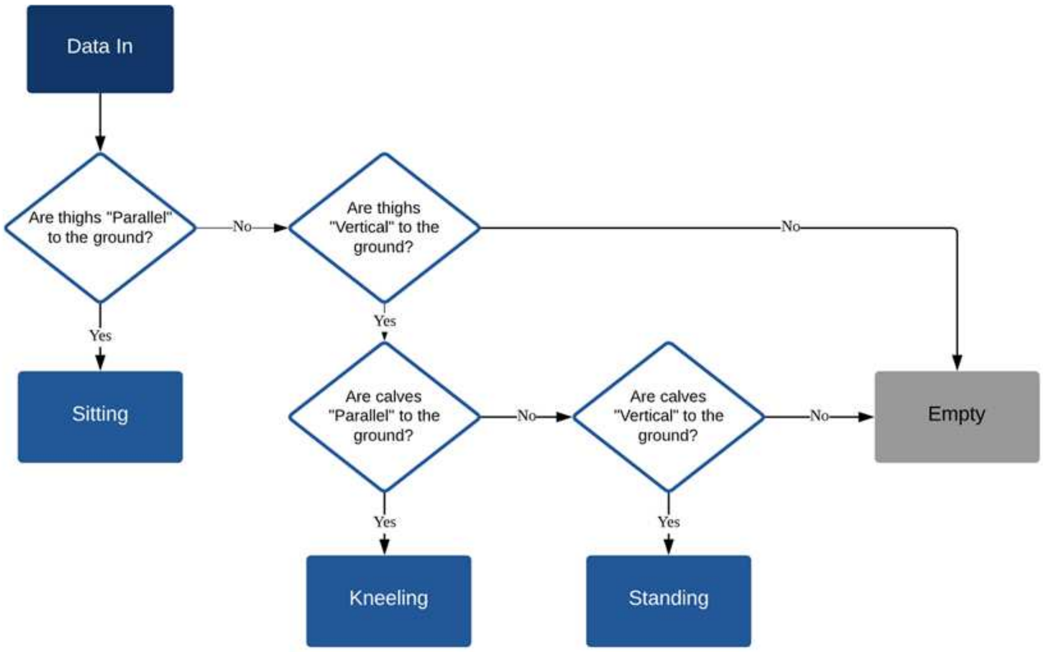


Figure 8. Flow chart for distinguishing lower body state by angles. This flowchart was used to specify the production rules for recognising the status of the lower body state.

3.4.1.2 Upper body state recognition: For the identification of the upper body state, we check the inclination angle of the spine, the angle between the upper arm and the horizontal plane, and the angle between the forearm and the horizontal plane, as shown in Figure 9. After calculating the inclination angle of the spine (that is, the angle between the spine and the positive direction vector of the Y-axis), it is compared with the set threshold size to determine whether the human body is bent. Considering that the human body is erect, there will be slight forward and backward tilting, so the threshold is set to 35 degrees. When the angle is greater than 35 degrees, the human body is considered to be in a bent state.

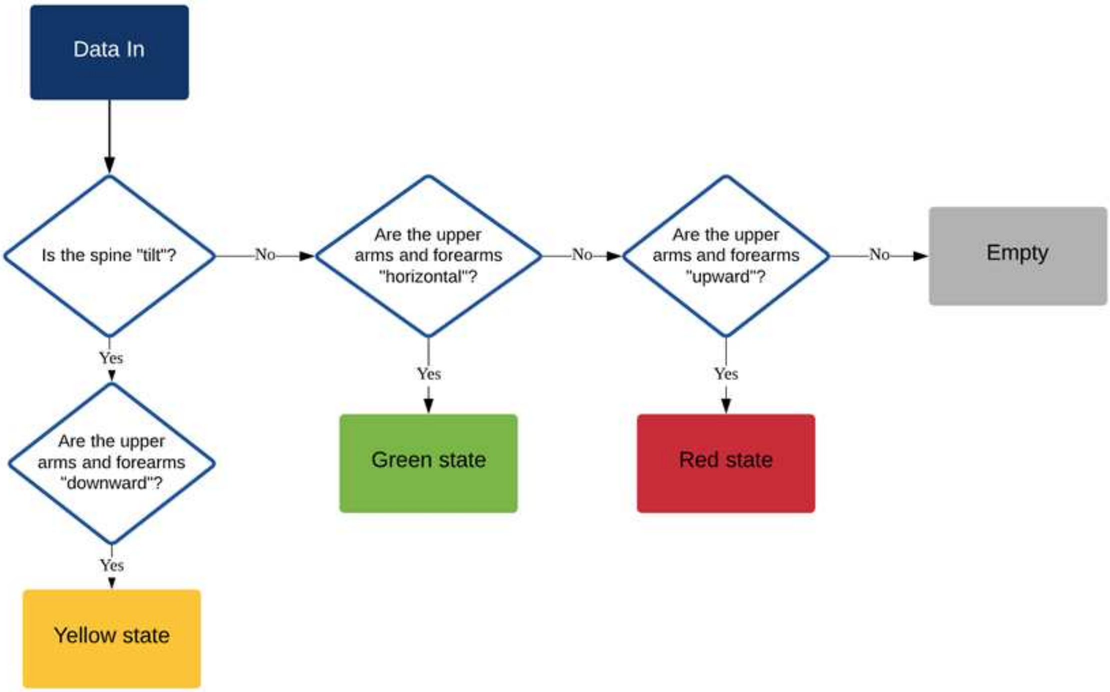
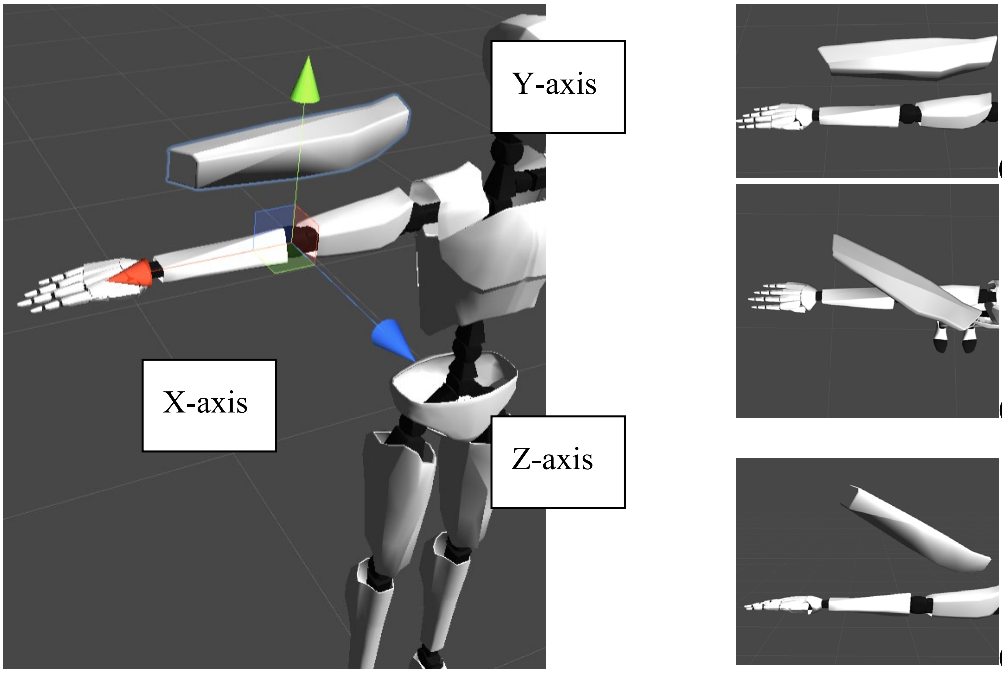


Figure 9. Flow chart for distinguishing the upper body state by the angle. This flowchart was used to specify the production rules for recognising the status of the upper body state.

When checking the state of the arm, we use the function on the Euler angle in Unity3D. For a frame of reference in three dimensions, the orientation of any coordinate system can be represented by three Euler angles. Correspondingly, "eulerAngles" is a Vector3 variable in Unity3D and all three values in the variable range from 0 to 360. The hierarchical relationship is ZXY, that is, the innermost layer is the Z-axis, the middle layer is the X-axis, and the outermost layer is the Y-axis. The initial state of the right forearm of the robot model is shown in Figure 10 (a) to demonstrate Euler angle rotation. Figure 10. (b), (c) and (d) correspond to the robot model rotating only about the X-axis, the Y-axis and the Z-axis by 45° respectively.

For the world coordinate system, the right forearm is in the positive direction of the Y-axis due to the establishment of the initial model. Therefore, the rotation of the model only about the X-axis can be understood as the rotation of the forearm skeleton, the arm is fixed in one position, and the rotation of the forearm when the wrist is only rotated. Rotation of the model only about the Y-axis can be understood as the rotation of the forearm in the horizontal plane. Rotating the model only about the Z-axis can be understood as the "up and down" movement of the forearm.



(b)
(c)
(d)
(a)

Figure 10. The sample model is not rotated in (a), the sample model is rotated 45° about the X-axis in (b), the sample model is rotated 45° about the Y-axis in (c), and the sample model is rotated 45° about the Z-axis in (d). It should be noted that achieving some of the rotations in the figures above could quickly lead to intense muscle fatigue.

In reality, whether the arm is active above, in front or below, the range of motion of the forearm is larger than that of the upper arm. In other words, the determination of the angle between the upper arm and the horizontal plane is more stringent. Therefore, the range of the Euler angles corresponding to the Y-axis which is determined to be the "front" state is also larger. Since the initial model and state of the left arm of the robot model is different from that of the right arm, its orientation is in the negative direction of the Y-axis. As a result, it is in the "upper" state and the angle of rotation around the Y-axis is just opposite to the right arm. The determination range of each state of the upper body is shown in Table 5.

Table 5. Some definitions about the direction of the arm

	Right forearm	Right upper arm	Left upper arm	Left arm
“Upward”	10-90	30-90	270-330	270-350
“Horizontal”	0-10, 320-360	0-30, 320-360	0-40, 330-360	0-40, 350-360
“Downward”	270-320	270-320	40-90	40-90

3.4.2 Weight recognition: This section of the paper focuses on the processing of the original EMG signal obtained from the Myo armband, the analysis of the EMG signals obtained when carrying different weights, and the estimation of weights using the data from the Myo armband. The Myo armband collects signals at a high frame rate of 200Hz from eight channels. The absolute values of the data from the eight channels are summed up into a single value. This value is then used as a reference for muscle stimulation level. However, the signal from the Myo armband is very noisy and difficult to analyse as shown by the blue lines in Figures 11 and 12. As a result, the signal needs to be filtered.

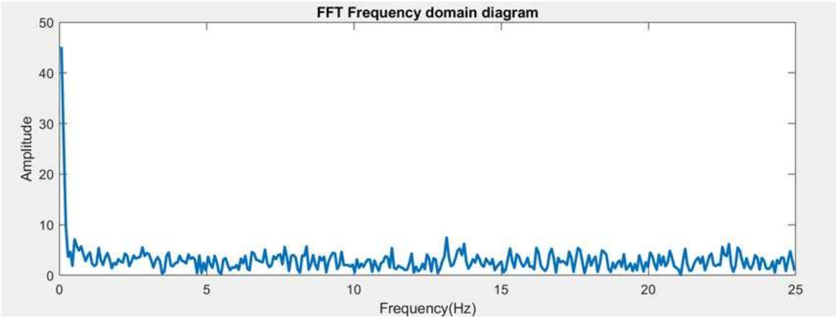


Figure 11. Frequency domain diagram of the original EMG signal

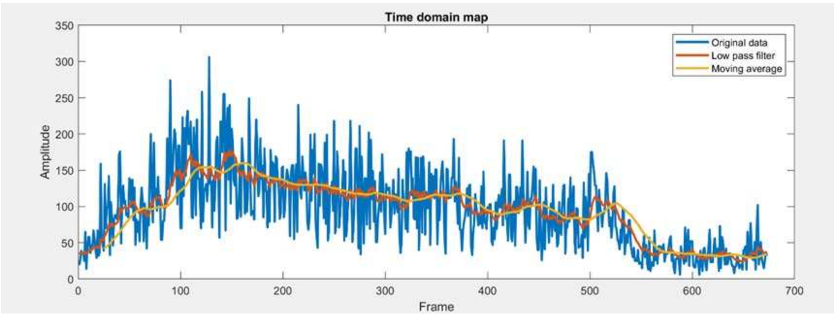


Figure 12. Time-domain diagram of EMG signal

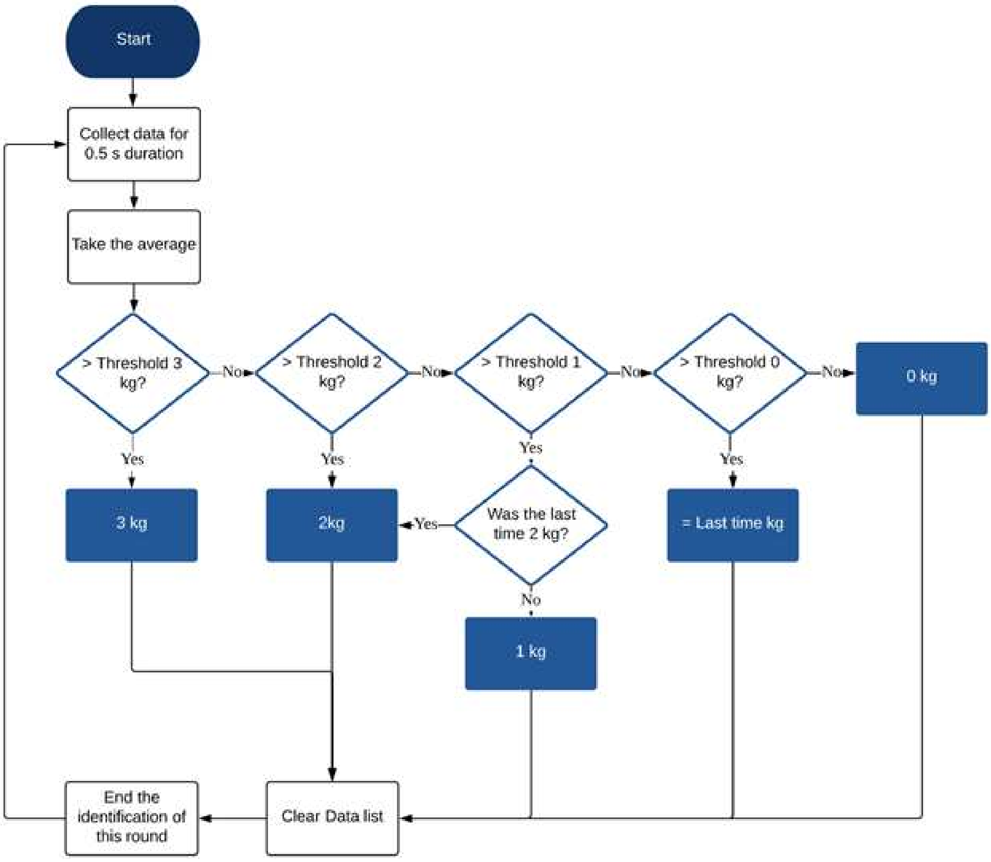


Figure 13. Weight identification flow chart. This flow chart was used to specify the production rules for weight recognition

A digital first-order low-pass filter (Equation 1) was used to ensure that low-frequency signals can pass through normally while the high-frequency signals exceeding the cut-off frequency were cut off and weakened.

$$Y_n = aX_n + (1 - a)Y_{n-1}$$

Where X_n is the current sampled value, Y_{n-1} is the output value after the last filtering, Y_n is the output value of this filtering and a is the filter coefficient (Equation 2).

$$a = \frac{\Delta T}{\Delta T + \frac{1}{2\pi f_c}} = 0.06 \qquad 2$$

Where ΔT is the sampling period which is 0.02 seconds, f_c is a cut-off frequency which was set as 0.5 Hz in order to filter out part of the noise. The curve of the EMG signal after filtering by the low-pass filter is significantly smoother, as shown by the red line in Figure 12.

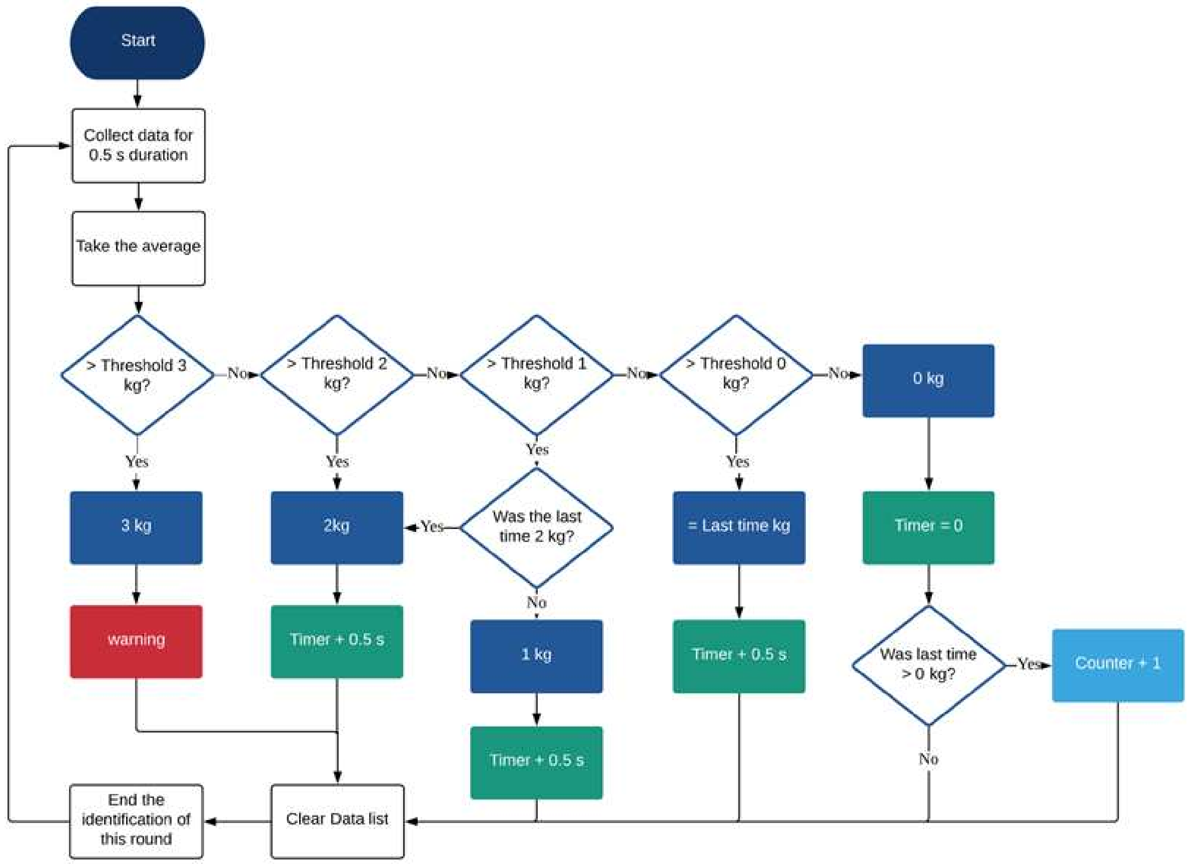


Figure 14. The flowchart after adding a timer

In order to make the program better judge the size of the hand bearing and the timing function of the program, the output value of the first 25 samples after the first filtering is selected every 0.5 seconds (in fact, 25 is also the number of all the values acquired within 0.5 seconds).
We find the average of them, as the value at time *t* and use this value to carry out the weight judgment. 0.5 seconds can also be considered as the second data smoothing of the filtered signal, as shown by the yellow line in Figure 12. The 25 samples are chosen because although the more values are selected, the smoother the curve will be, but the delay will be higher, and

the 0.5-second refresh rate is within the acceptable range of system design. Using production rules as defined by Figure 13, is was possible to build a weight classification algorithm to recognise which weight a worker was carrying. In order to ensure that different users can use the system, a calibration procedure was performed after the Myo armband was worn. The details of the calibration are discussed in the results section.

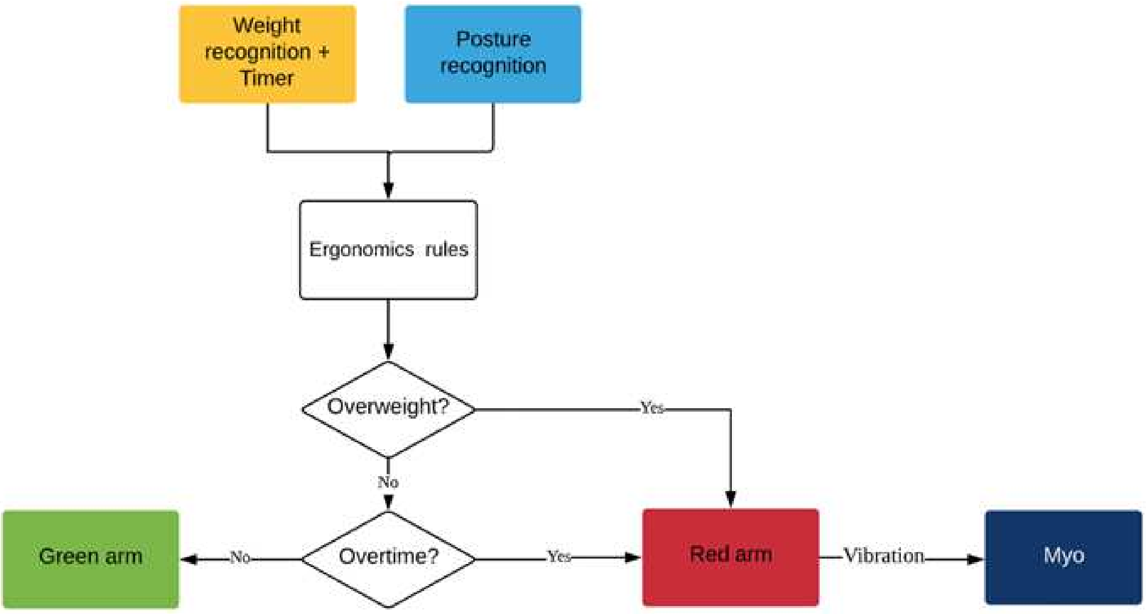


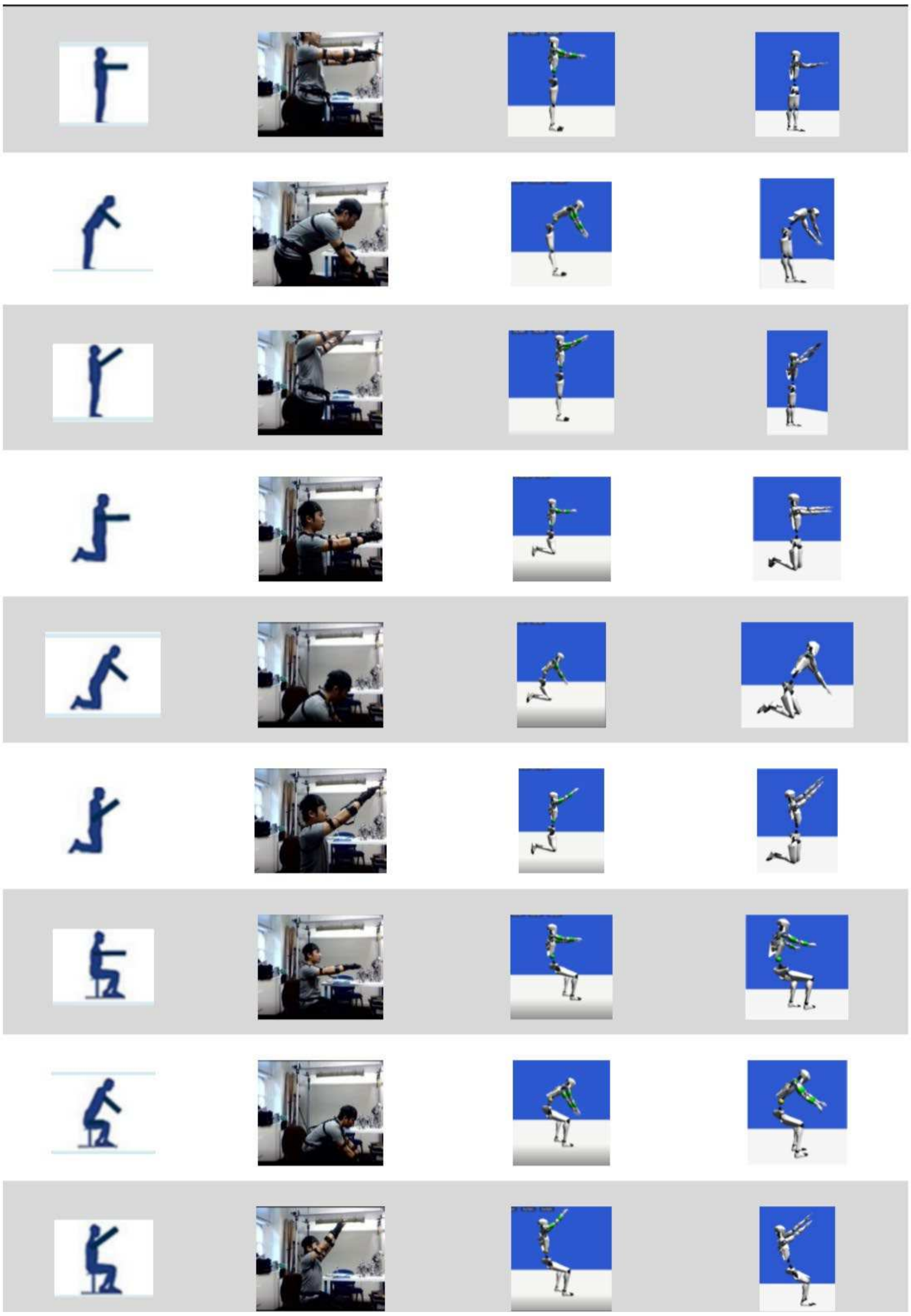
Figure 15. A flowchart showing the fusion of posture and weight recognition

3.5 Fusing posture and weight recognition information for achieving real-time ergonomic assessment: According to the requirements of the aerospace ergonomics case study, a weight cannot be held for longer than a duration. Also, the safe duration varied depending on the posture. As a result, there was a need to fuse the information from both the posture and weight recognition modules into a cohesive system. In order to achieve this, firstly, a timer function was added to the flowchart of Figure 13 in order to realise a time based weight recognition system (Figure 14). The fusion of posture and weight recognition information are shown in Figure 15. The fusion was achieved through the use of ergonomics rules obtained from the knowledge on weight, duration and postures.

3.6 Production execution and feedback to the user: In order to provide feedback to the user, we make use of both tactile vibration in the Myo armband and visual buffer via the Physics based Musculoskeletal buffer. When the system recognises one of the nine types of standard predefined postures, the corresponding pose picture is displayed in the lower-left corner of the user interface. If the current posture is not defined, it will be displayed as a small white square. When the weight or time of the hand does not meet the current posture standards required by case study Company, the green game objects on the arms of the robot model used to symbolise muscles turn red. In this way, an operator can playback and review the activities performed during an assembly and see how often ergonomics rules are broken. This could provide feedback to the worker on areas for improvement.

Table 6. The results of posture recognition.

Booklet posture	Real life posture	Visual Buffer Representation	Posture Recognition Result

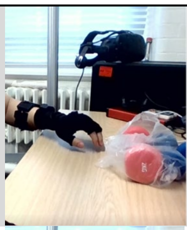
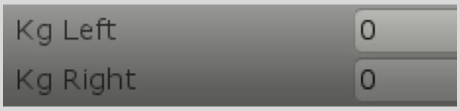
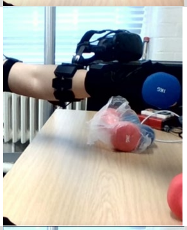
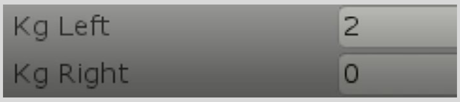


4.0 Results

In this section the results obtained from the implementation of the architecture are discussed. Firstly, the posture recognition is detailed, followed by weight recognition and then the results obtained from the fusion of the posture and weight recognition.

4.1 Posture Recognition: Using the upper body and the lower body states, the posture of the entire human body as well as its ergonomics compliance was determined according to the requirements of the leading aerospace manufacturer's ergonomics booklet. The result of the posture recognition was displayed in the visual buffer using pictures related to the recognised posture (see Table 6).

Table 7. The results of weight recognition

The object weight (kg)	In real life	Result of recognition
0		
1		
2		
3		

4.2 Weight Recognition: The system was able to recognise the function of picking up objects of 1 kg, 2 kg and 3 kg by hand. The results of the test are shown in Table 7. Each user was equipped with two Myo arm bands on each arm. By importing the two Myo EMG data into the Unity environment at the same time, it was possible to identify the sum of the weights in the left and right hands. Figure 16 shows the forearm EMG signal of the hand of one user taking different weighted objects.

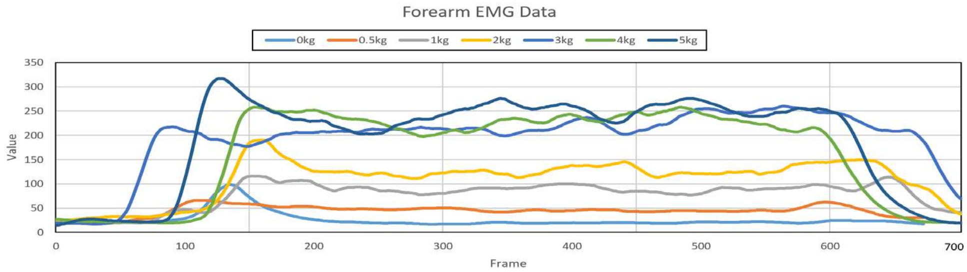


Figure 16. The forearm EMG signal diagram of the hand taking different weight objects

The EMG data obtained from the forearm muscle was stable at around 25 at rest state. The value was about 50 when carrying 0.5 kg, 95 when carrying 1kg and 125 at 2 kg. When the right hand carried 3 kg, 4 kg and 5 kg dumbbells respectively, the curve fluctuates greatly and the demarcation between these weights was not clear cut.

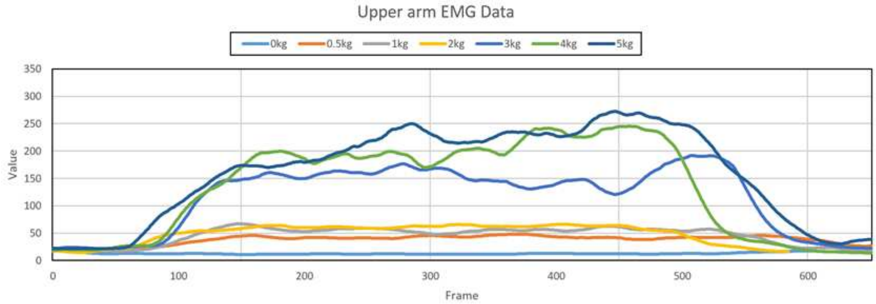


Figure 17. The upper arm EMG signal diagram of the hand taking different weight objects

When the Myo was moved to the upper arm, in order to find out if it was possible to improve the demarcation results, the resulting EMG data was produced as shown in Figure 17. According to the data obtained from the upper arm, the muscle signal at the upper arm position does not change significantly when no weight is taken on the hand. When the objects of 0.5 kg, 1 kg and 2 kg were carried, the value of the EMG signal kept at about 50. When the weight carried by the hand was 3kg, the value of the EMG signal suddenly increases to 150 or more. It is also worth noting that when an object of 3 kg or more was lifted with only one hand, the muscles were put under a lot of stress. According to the case study's ergonomic booklet, a load of 5kg is the maximum load-bearing standard for all postures when using both hands to carry objects. As a result, this work added a new rule to the original rules to specify that no matter what posture, the weight of one hand should not exceed 3kg. Based on the above, it was concluded that the Myo armband can be placed on the forearm to obtain a suitable range of recognition of the following weights: 1 kg, 2 kg and 3 kg.

4.3 Multi-person test and analysis: In order to see if the characteristics of EMG signals are similar when different people take the same weight of objects, five people were randomly invited to participate in the test. According to Figure 18, it can be seen that when different people carry the same weight (2kg) in their hands, the collected EMG signals have different levels of magnitude. This may be due to various reasons such as the length of the forearm, the thickness of the forearm, the specific position of the Myo armband, muscle strength, muscle mass, or muscle fatigue differences in the testers. Four of the five testers had similar ranges of EMG signal values. However, the tester 3's EMG signal value was significantly higher than the EMG signal value of the rest of the testers. Furthermore, it can be seen that the EMG signals are also different for the left and right arm even when the same weight is carried (Figure 19).

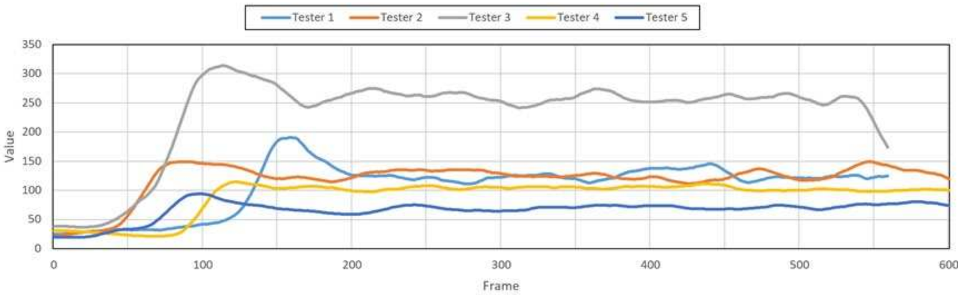


Figure 18. EMG data from five different testers carrying a 2kg weight

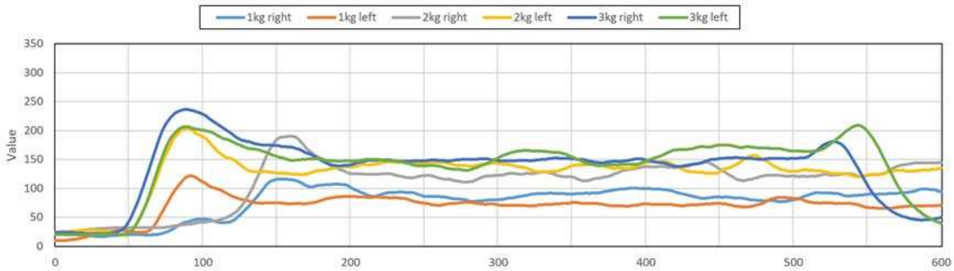
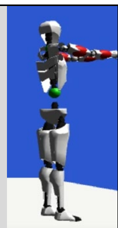
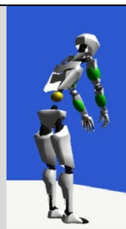
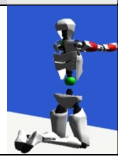


Figure 19. EMG data for various weights carried by the left and right arm.

4.4 Calibration for Different Users: Based on the results of the multiplayer test, it was inaccurate to use a uniform threshold to distinguish the weight of the hand from different people. Even for the same person's left forearm and right forearm, it was necessary to set different thresholds. Towards this a calibration procedure was designed for use at the beginning of a work shift. Taking the left-hand threshold setting as an example, when the user wears the Myo armband, the left hand picks up standard weights of 1kg, 2kg as well as 3kg and then remains motionless. During this time, 3 seconds of EMG data is recorded for each weight. The average of the recorded data for each weight is then used as a threshold. After all the thresholds have been set, the system was capable of identifying various weights.

Table 8. Results of real-time assessment of manual tasks

Posture	Weight	In real life	0 s	1 s	3 s	3.5 s	End
	1 kg + 1 kg						
	1 kg						

4.5 Results of fusing posture and weight recognition information for the real-time assessment of manual tasks: An experiment was conducted to test if the system was capable of tracking the ergonomics of workers in real time. To achieve this, the flowchart in Figure 15 was used. Two groups were selected for testing. In the first group, 1 kg of objects were picked up by the left and right hands, and the second group picked up 1 kg of object only with the right hand. The results of these experiments are shown in Table 8. It can be seen that after 3 seconds, there the visual indication changed from green to red to indicate that ergonomic rules were being broken for this task. When the object is lowered, the arm muscles returned to green again.

5.0 Discussion and limitations

The benefits and implications of applying wearable sensors in manufacturing are broad for both academics and practitioners. For industrial practitioners, it has been observed that human errors drastically affect the profitability of companies. This is because human errors lead to product recalls which damage the reputation of the affected company as well as erode profit margins. In addition to this, space, cost and time is spent setting up a test station in order to ensure that manually assembled products are given a thorough test before shipping to customers. Of course one particular solution is provided by using automation, especially in situations where the tasks are highly repetitive. However, there are still a number of tasks where it is not possible to automate due to complexity and inherent dexterity required to facilitate variations that occur during the task. As a result, there has been an increase in research aiming to identify or develop wearable sensors and processing architectures that could be applied to get manual assembly progress directly from humans as well as understand the factors that contribute to human performance. Such systems will ensure that errors are caught earlier in the manufacturing process thereby potentially reducing the error rate and possibly the need for a test station in [8]. Furthermore, in [1], the authors highlighted that the applications of wearables could have a high beneficial impact on the work being digitised while having little to medium limitations. The limitations cited included pressure spots on the operator's body which could be alleviated by taking regular breaks.

In this work, a Cognitive Architecture for Wearable Sensors (CAWES) inspired by the ACT-R framework has been presented. This architecture was used to guide the development of a wearable cognitive system to aid in keeping track of the ergonomics of workers during various tasks. Unlike previous work [41][42], CAWES is a cognitive architecture that fuses data from multiple wearable sensor systems including EMG signals from wearables to enable recognition schemes for the weights carried by wearers as well as the postures being used during activities. This was achieved by converting the ergonomic requirements of a case study into production rules for the cognition architecture. Through the use of these embedded production rules, it is shown that the architecture was able to provide feedback to wearers with regards to task based ergonomics compliance. The production rules enabled the development of recognition rules for various postures assumed by workers as well as the weights carried by them. By fusing these recognition rules with a time function, it was possible to inform workers when an ergonomic rule was broken. In general, the results of human posture recognition are encouraging. After adding the calibration procedure, the accuracy of the weight recognition system using Myo armbands improved by up to 90%.

However, this system has limitations and shortcomings. First, it was discovered that if the hand performs unnecessary gestures and the arm muscles were in a non-relaxed state, the recognition of the weight system may not be accurate. Secondly, the experiment only tested standard known weights of objects and did not perform more comprehensive tests on different objects in the actual working environment. Therefore, the applicability of the system to industrial environments has not been fully proven.

Thirdly, the experiment recognises the weight of the object in hand by always grasping the object with the palm down. However, if the object is lifted in the upward position of the palm, some of the muscle stimulation in the forearm will be shared with the upper arm, thus reducing the value of EMG signals collected by the Myo armband on the forearm. Fourthly, due to the complexity of muscle signals, when the weight carried by the hand exceeds a certain weight, the EMG signals collected on the forearm alone are not enough to clearly distinguish its weight. Also, when analysing the EMG signal obtained by Myo armband, our system incorporates low-pass filtering. We do not exclude that there is a possibility that other kinds of relationships between the EMG signal and the weight exist in the high-frequency signal.

Furthermore, the EMG signals could be affected by a number of factors including muscle fatigue, age, height, ethnicity and strength. Nevertheless, these are challenges that have also been highlighted in other related work such as in [43]. These shortcomings could be addressed through the use of more sophisticated systems than the production rules of our architecture. This might require combining the production rules with more sophisticated techniques such as applying neural networks, deep learning or swarm evolutionary computation techniques [43][44][45]. Such research might shed light into the neural mechanisms for data fusion and decision making in the Basal Ganglia as depicted in the ACT-R architecture of Figure 2.

In this work, the visual buffer was represented using Unity3D. The use of Unity3D enables the playback of worker activities on the shopfloor to help individual workers improve their posture. Furthermore, the use of the Visual Buffer could be used to run multiple hypothesis of the assembly process before physical runs. This could be used by managers to digitally certify activities before deployment onto the shopfloor. The manual buffer was used to acquire data from sensors as well as configure tactile feedback to workers. However, the tactile feedback needs to be configured empirically to provide appropriate feedback. This is because the vibration feedback of the Myo armband may distract workers in the assembly process, thus affecting the efficiency of assembly and even causing errors in the assembly process. Furthermore, the use of wearable devices involves the collection of personal information from workers. This may make workers feel that their assembly efficiency is being monitored and may reduce uptake of the developed system.

6.0 Conclusion and future work

The aerospace industry is still heavily reliant on manual labour in various stages of an aircraft's assembly. For such manufacturing systems, the issue of musculoskeletal injuries severely limits the output of such a system. Workers in such manufacturing systems could benefit from a real time system that can inform them when their posture is detrimental to their long term health.

In this work, inspired by the Adaptive Control of Thought—Rational (ACT-R) architecture from psychology, we presented a Cognitive Architecture for Wearable Sensors (CAWES). According to [28], *"Cognitive architectures are a part of research in general AI, with the goal of creating programs that could reason about problems across different domains, develop insights, adapt to new situations and reflect on themselves. ... To this end, cognitive architectures attempt to provide evidence (to) what particular mechanisms succeed in producing intelligent behaviour and thus contribute to cognitive science."*

The CAWES architecture potentially provides a framework and a shift in the paradigm of how real time ergonomics assessment systems will be developed for use in future manufacturing systems. This is especially relevant as human-in-the-loop and human-centred systems become more commonly used in manufacturing. The architecture inspires:

(i) how data should be processed. This is especially true when considering multiple data streams from different sensing modalities,
(ii) a framework that highlights how production rules and continuous learning algorithms that reason across different ergonomics tasks and adapt to new situations could be created and embedded in human-centred systems.
(iii) how digital twins (via visual buffer in the architecture) and multi-sensor wearables should interact to ensure real time ergonomics safety and human comfort during manual intensive tasks [46].

The framework offers a step towards architectures that would be able to reflect on the performances of workers in order to elicit new rules that further improve safety, productivity and efficiency of workers. Currently, most approaches for real-time ergonomics assessment have been ad hoc and this architecture provides a starting point for enabling the research community to have a concentrated effort towards building improved human-centred systems.

In this work, the CAWES architecture is able to recognise postures, weights as well as duration of tasks performed by workers. The architecture uses embedded production rules to process and fuse multiple wearable data streams in real time as well as provide tactile feedback via vibrations in the wearable worn by the worker. The tactile feedback was used to inform workers when an activity was not conducive for them. As mentioned earlier, the ACT-R architecture was used to inspire the information flow, processing and fusion of data streams in the CAWES architecture. However, it should be noted that not all aspects of the ACT-R architecture were used in this research.

Furthermore, although the results of the proposed architecture are promising, experiments were conducted in laboratory settings. As a result, further work is required for fully validated application in actual assembly processes. Nevertheless, the data derived using the proposed system could be used to analyse a shopfloor. The data could reveal various unnecessary movement actions within an assembly activity; the reasoning behind such actions, when identified by the approach, could inform future process improvement programs. Additional future research targets include the further application of cognitive architectures for the processing and fusing of data provided by wearable sensors. By developing systems in this way, the psychological knowledge inherently present in the cognitive architecture could also be exploited and provide bootstrapping mechanisms and additional basis for the development of insight generating algorithms.

Additionally, cognition is a holistic phenomenon which includes the acquisition of new rules as well as the transfer of previously learnt rules to new scenarios or context. As a result, when creating new artificial cognitive systems, the embedding of prior known production rules as well as acquiring new ones from the domain of interest (through learning) are all part of a complete cognitive architecture. In this work, we focused only on embedding rules from an ergonomics handbook into a cognitive architecture in order to meet official guidelines on repetitive working in the aerospace sector. These rules are part of an official standard that needs to be abide by. As a result, it was necessary to start with these rules in developing the production memory module of the CAWES architecture. In future work, it will be interesting to see how other rules could be extracted autonomously (through machine learning) from worker performance data. This would form part of a continuous learning scheme in the CAWES architecture. The development and application of the CAWES architecture as discussed in this work, provides us with initial steps towards achieving this.

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