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Automated Musculoskeletal Disorder Risk Assessment

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(ii) Contents

(iii) Abstract

The project has developed wearable sensors that obtain musculoskeletal data from workers, analyse tasks and generate scored manual handling risk assessments. The sensors deliver data to a simple-to-use app with the only one task for the user being to start and stop analysing the activity.

The app works on phones and tablets using a developed machine learning system to analyse data and present it on intuitive screens in simple report formats.

The sensors measure acceleration and orientation, and gather data that the application uses to compute the risk assessments. The risk assessments can be shown while the task is being performed when the app is connected to the sensors, allowing real time education and training based on the assessment. The sensors can also record data on their own, without the mobile device being present, allowing automated assessments to be performed after the task has finished.

Testing in the coal production environment has proved the system and very positive feedback has been received from wearers of the sensors who report no interference with work and no discomfort. Post hoc replaying of video and risk assessment data has demonstrated the value of the system in worker engagement and manual handling solution development.

The risk assessment method employed by the application is based on and is closely aligned to the Australian Model Code of Practice - Hazardous Manual Tasks 2016 and its predecessor codes, guides and national standard. This method has been extended to address a factor that limits application by both expert and casual users; the consequence scoring in the risk estimation calculation has been populated using extensive injury clinical and claims data. This standardised method results in the provision of ranked scores based on type of injury risk and enables use alongside other Work Health & Safety risk-scoring.

(iv) Executive Summary

Project objectives

The aim of the project was to develop a mobile application (app) that enables low-cost, replicable, automated musculoskeletal disorder (MSD) risk assessments in the mining industry.

The objectives were to:

- Develop and prove the validity of a mobile app that uses computer learning and recognition algorithms to compute a manual handling risk assessment using data captured by wearable sensors.
- Enable cost saving through an automated risk assessment process conducted by non-specialists.
- Improve the consistency of MSD risk assessments across a wide variety of activities.
- Collect data from a wide range of MSD risk assessments to improve knowledge transfer and guide targeted controls to reduce injury rates, and improve injury outcomes.

Main findings and conclusions

JointAction has developed wearable sensors that obtain musculoskeletal data, analyse tasks and generate scored manual handling risk assessments.

The sensors deliver data to a simple-to-use app with only one task for the user: to start and stop analysing the activity. The app works on phones and tablets using a developed machine learning system to analyse data and present it on intuitive screens in simple report formats.

The sensors measure acceleration and orientation, and gather data that the app uses to compute the risk assessments. The risk assessments can be shown live when the mobile app is connected to the sensors when the task is being performed, allowing real time education and training based on the assessment. The sensors can also record data on their own, without the mobile device needing to be present, allowing automated assessments to be performed after the task has finished.

The risk assessment method employed by the application is based on and is closely aligned to the Australian Model Code of Practice - Hazardous Manual Tasks 2016 and its predecessor codes, guides and national standard. This method has been extended to address a factor that limits application by both expert and casual users; the consequence scoring in the risk estimation calculation has been populated using extensive injury clinical and claims data. This standardised method results in the provision of ranked scores based on type of injury risk and enables use alongside other Work Health & Safety risk-scoring.

The risk assessment process has been verified by human expert observation and assessment of the manual handling tasks being app-assessed. Satisfactory correlation of risk scores has been achieved but the differences require further investigation.

It has been found that the automated system brings a high degree of reliability to the assessment process. The measure of validity of the assessment is based on comparison with human assessment. Two issues have been identified; 1. The human assessment is subjective and while using the Australian Model Code of Practice assessment process the human introduces many assumptions and a degree of bias based on knowledge of the task. This means the reliability of the human assessment is lower than that of the app and in any given assessment there may be disagreement between the app and human-calculated risk score; and 2. The computing rate of the app makes it better able to quantify repetitious movement than the human.

Further work is required to assess the ways in which subjectivity is introduced into the human use of the Australian Model Code of Practice risk phrases and how this may be addressed within the app.

The correlation between the app and human assessments means that risk assessment scores may be considered valid and informed choices about the necessity for risk controls may be made.

Industrial applications

The automated musculoskeletal disorder (MSD) risk assessment system has been designed for manual handling risk assessment in the coal industry. Industry pilot trials have demonstrated its useability and certification for underground use is planned.

All manual handling tasks require risk assessment and the automated system will reduce costs, increase consistency of assessments and facilitate consultation on risk reduction measures. Use in the coal industry will lead to cost savings and more efficient use of health and safety and supervisor personnel’s time and capacities in work related musculoskeletal disorder prevention and injury management.

(v) Recommendations

It is recommended that during the post-project extended industry trials and verification:

- Certification for underground use of the Automated Musculoskeletal Disorder Risk Assessment system is obtained.
- The definitions of the categorical assessments used in human Musculoskeletal Disorder risk assessments are improved to decrease subjectivity and enable the increased precision in the machine interpretation of the processes.
- The musculoskeletal injury claims outcomes database used in the Automated Musculoskeletal Disorder Risk Assessment system for the calculation of a consequence score is enhanced to thereby enable coal industry-specific and potentially company and site-specific data to be used to provide better estimates of the costs of risk and cost benefit of risk controls under consideration.

(vi) Body of Report

Developmental Stages

Introduction

Wearable motion sensors incorporating an accelerometer, magnetometer and gyroscope have been available commercially for some time and are used in the sports sciences. Adoption of these for use in musculoskeletal risk assessments in the coal industry required development of algorithms that would firstly enable aggregation of orientation data from multiple sensors and secondly the translation of that aggregated sensor data to information that can be related to manual handling risk phrases. Simultaneously it was necessary to develop a consequence scoring system that could be married with the risk phrase scoring to deliver an overall risk score.

The functionality of the sensors and the validity of the algorithms required proving before on-site trials could commence. This stage of the project was referred to as proof-of-concept. Following the proving process an initial site pilot trial was conducted; the systems were refined and then further site pilot trials conducted.

At the conclusion of the project, extended site trials will commence prior to development for commercialisation.

Stage 1: Proof-of-concept research

The proof-of-concept determined that commercially available sensor hardware could deliver sufficient accuracy to compute absolute orientation and, in turn, record and stream the captured data to an app. It was found that commonly used mobile devices had sufficient processing capability to interpret and analyse the incoming data in real-time and the most appropriate methods of interpretation and analysis of incoming data for use by the app were identified.

It was acknowledged that a fundamental requirement for any resulting commercial application would be ease-of-use in the field. As such, a determination was made that the sensor units must communicate their data (either streaming, or sending after recording it internally) with the receiving mobile device via the Bluetooth LE protocol. Bluetooth LE requires no complicated pairing (eliminating problems with the sensors being paired to the wrong device), is very power efficient (allowing the sensors to stream data to the mobile device all day) and allows several devices to be connected simultaneously.

To compute orientation (attitude), the sensor device must provide its vector with respect to gravity and vector with respect to compass heading. Using the two vectors, an orientation with respect to Earth can be computed (an absolute orientation for this case). The vectors are provided by the accelerometer and magnetometer respectively. In practice, the two sensors alone will produce a noisy attitude result because the accelerometer is subject to the random vibrations that occur when worn, and both do not detect fast changes in orientation. A method to correct both shortcomings is to combine another type of sensor data, in this case from a gyroscope. Gyroscope data is used for fast and extreme changes in orientation, while the accelerometer and magnetometer provide the base absolute heading with respect to Earth. This is known as sensor fusion.

Development progressed with sensor units that satisfied the Bluetooth LE and the attitude computation requirements. Initially, Texas Instruments (TI) Sensor Tag development kits were available and used for development (Mk 1 sensors). These units have a 3-axis accelerometer, 3-axis magnetometer, 3-axis gyro and Bluetooth LE radio and stream their sensor data over a Bluetooth LE connection at a rate of 25hz. Using these sensors, development of a testing “state model” of the risk assessment system was started, along with a Bluetooth communications programming library, and implementation and adaptation of 2 sensor fusion algorithms for testing.

Linear Quadratic Estimation has been used in various guidance and navigation systems used in other fields to combine multiple types of noisy and/or drifting sensor data. This decreases the inaccuracies of each individual sensor, and is the most mathematically optimal filter and was investigated for use. However, during the project proof-of-concept stage the much simpler Complimentary Filter process was investigated and found to also provide sensor fusion and have less computational requirements. Given the desire to enable real-time analysis on mobile devices that have finite computational capacity, the Complimentary Filter process was attractive and development work was switched accordingly.

A prototype app was developed for iPad which served as a test-bed for the integration of the Bluetooth communications library, sensor streaming, attitude calculation and state analysis. Through testing of the system, it became apparent that the TI Sensor Tag development kits would not have the capability to serve further development of the system because they did not permit adjustment of the streaming rate (locked at 25hz), lost data packets when streaming from more than one sensor on a device (3 sensors are needed for sensor fusion), and the magnetometer was only accurate enough for a general north heading while accurate attitude calculations require accurate compass readings.

Replacement sensor candidates that satisfied the project requirements were investigated and Hexiwear Kinetis, Mbient Lab Metawear and Stt-Systems Inertial Motion were identified. Hexiwear Kenetis was chosen for the next test-bed (Mk 2 sensors) due to its open platform i.e. the Firmware for the sensor was available and opensource and permitted programming within a wide range of capabilities. The units were also low cost and possessed potentially useful features such as OLED display and haptic feedback. The use of this sensor required modification of the Bluetooth communications programming library to accommodate the different command interface from the previous sensors.

Programming work was undertaken to enable the test iPad application to use several different machine learning techniques to identify the posture and orientation of the person wearing the sensors, which would, in-turn, enable the allocation of numerical values against risk phrases drawn from the Australian Model Code of Practice, i.e. the equivalent of populating a risk assessment template.

Two machine learning algorithms were tested; (1) a shallow neural network and (2) a support vector machine. Both were tested in three configurations: (1) raw sensor data being fed into the algorithm; (2) sensor attitude being fed into the algorithm and; (3) assessment criteria items being fed in to the algorithm. In principle, the algorithm looking at the complete sensor data would provide the most consistent detection of states, however in practice there were problems with false positives tracking the transitions of states and confusion between similar states. With more opportunity for the collection of training data to improve the machine learning models, these problems may be able to be resolved, however with the data and resources at hand, the configuration of the machine learning algorithm analysing the degrees of the assessment criteria items produced the most consistent detection and tracking.

To allocate numerical values, the app had to be able to identify when items in the risk assessment occur, record their values and durations, and keep track of them. For example, for the bending and twisting section in a risk assessment, the app needs to identify that both a bend and twist are occurring (the machine learning aspect) and determine the magnitude of the movement and the duration (e.g. > 40 degrees for over 2 minutes). For the identification, the system needed a number of reference data for the various criteria.

Progress with the mk2 sensors had been slow and difficult; although the firmware for the sensors was open and documented, the CPU on the sensor devices was not powerful enough to stream data from 5 units at the required rate. Although it was theoretically possible to disable other sensors and services on the device consuming CPU cycles, the design of the system was such that that the drivers for the sensors were interdependent and this meant significant work would be required to change the configuration.

At this stage in the project, Mbient Lab released a new sensor unit which incorporated the sensor fusion on-chip, reducing the amount of data that needed to be streamed and recorded, had enormous internal storage for recording sensor data, and had a very fast CPU. Due to the difficulty of modifying the mk2 sensor firmware, the system was changed to incorporate the Metamotion R sensors (mk3). The change meant some reworking and simplification of the Bluetooth programming library and modification to the detection system.

Refinements to the state recognition and processing algorithms were continuous to improve the accuracy and consistency, along with further training of the machine learning algorithms to improve the state recognition for more varied combinations of assessment criteria. Magnetometer calibration was an ongoing usability issue because re-calibration was needed every 30 to 40 minutes and also when environments changed. A request to the manufacturer led to a sensor firmware change and this allowed continuous adaptive calibration solving the calibration issues (mk4 sensors).

At the same time as developing the sensors and the software behind the app, the user interface with the app was developed to enable intuitive operation of the system and to display risk assessments live when the app is connected to the sensors and the task is being performed. The latter feature is based on a desire to use the system in education and training i.e. allow workers, supervisors, managers and health and safety personnel to see what elements of tasks expose people to elevated risk levels and facilitate discussions around risk control measures.

Work was undertaken to develop the consequence scoring element of the risk estimation calculation using extensive injury clinical and claims data. This standardised method enables the provision of ranked scores based on type of injury risk and enables use alongside other Work Health & Safety risk-scoring.

Stage 2: Prototype development & research

With the mk4 sensors and refined test app the first on-site visit for pilot trialling was scheduled. In preparation for the first on-site pilot trials, laboratory verification was conducted by fitting subjects with sensors who undertook a range of basic movements and adopted a variety of positions and orientations that were compared with reports generated by the app. Repeated trials enabled machine learning and validation of the app.

First onsite pilot (trial)

The first mine site piloting was conducted on 20 -22 December 2016 at BMA's open cut coal mine, Peak Downs. The aim was to gather data for subsequent verification through ergonomist task observation and assessment. Six maintenance tasks were observed and assessed:

- Moving Wheeled Platform & Steps Unit - Truck Maintenance Workshop
- Roller Change - Wash Area - ROM Conveyors – Preparation Plant - Processing Plant
- Scaffolding Equipment and materials handling - Preparation Plant
- Moving and Emptying Bins - Truck Maintenance Workshop
- Under truck Inspection - Truck Maintenance Workshop
- Filter Change - Truck Maintenance Workshop

Sensors were attached to a range of mine personnel undertaking the tasks. The subjects were of different ages and body types, one female, five males. Sensors were attached to the back, hip, head and wrist of the workers enabling assessment of discrete as well as combined movements such as simultaneous bending and twisting.

The sensors transmitted data to the App where the environment allowed, while simultaneously logging the sensor data to their internal memory. This enabled real time assessments including video collection as well as post hoc data analysis where workers were remote to the researchers. The app generated states were used to generate risk assessment reports.

Following the mine-site trial, expert ergonomist assessment of the collected data was undertaken for the purposes of validation and development of the app.

The sensors were subject to coal dust, coal mud, dirty and clean water and hot dirty engine oil and all functioned normally and it was found that battery life far exceeded needs. It was found that the posterior placement of the hip sensor meant that it got caught and pulled off in two instances of it being used and therefore re-positioning needed to be considered and a limitation was the use of the iPad in the wet areas but the data logging feature means that post hoc analysis is possible.

The data analysis from the first on-site visit data revealed several areas for improvement in the system; the timecode syncing between the sensors was not implemented correctly in firmware. This resulted in the recording of differing timecodes that led to significant amount of time being added to the analysis and synchronisation work. This problem was resolved by the manufacturer after changes and updates to the sensor firmware were requested. More significantly, it was apparent that the standard risk assessment criteria were not suitably defined for the automated system to make use of. This would be the major point of development leading up to the next stage.

First onsite pilot (trial) analysis

During the first onsite piloting trial there were short periods of automated data gathering with simultaneous videoing of the tasks. Data and vision/video capture were limited by the nature and circumstances of the tasks and the inability to observe the tasks throughout their duration given worker mobility and accessibility.

The videoed periods of the tasks with simultaneous auto data collection were typically less than two minutes with some up to five minutes. Video segments suitable for ergonomist analysis ranged from 20 seconds to two minutes in length. The video segments presented discrete sets of movements, postures and task actions. This made the ergonomist's work of recognising and categorising movement and posture and allocating frequency and repetition scores relatively straight forward.

It became apparent that, while there was general agreement between the automated (auto) and ergonomist (ergo) analyses of the tasks, there were discrepancies. It is likely that the differences between auto and ergo analyses are associated with the way in which the ergo brings to the process their experience of analysing a range of observed tasks and makes assumptions. It appears that the ergo assumptions increase with the quantum of repetitive and sustained categorised data. Where longer periods of work are observed and/or when the work observed has intense periods of movement, a variety of postures, and repetitive and sustained data generation across multiple risk categories, it is likely that the ergo allocates risk categories on the basis of the initial and the most clearly observable movement, postures, actions and loads. From this, the ergo estimates frequencies and durations. Contrastingly, the auto system undertakes objective, accurately quantified measurement of action durations and occurrences against elapsed time.

It is thought that the ergo analysis is subject to "Serial position effect". This is the tendency of a person to recall the first and last items in a series best, and the middle items worst. It has been found that recall accuracy varies as a function of an item's position within a study list. When asked to recall a list of items in any order (free recall), people tend to begin recall with the end of the list, recalling those items best (the recency effect). Among earlier list items, the first few items are recalled more frequently than the middle items (the primacy effect)[1].

The learning from the ergo-auto comparisons and the practical elements of the onsite trials led to further software and hardware refinements in preparation for a second workplace trial.

Stage 3: Development for industry trial

The comparison of machine versus human risk assessments at the completion of the first on-site trials identified a range of assumptions that are made in the human use of the Australian Model Code of Practice and other risk assessments checklists. Risk assessment in general is a highly subjective process. In respect to the risk phrases within the Australian Model Code of Practice assessment and like processes, it is apparent that the ergonomist makes many intuitive assumptions, uses experience and knowledge of a process or that of similar tasks and introduces prejudice. An automated system is, conversely, objective and completes assessments solely based on data received regarding the position of the sensors in space.

Work was therefore undertaken to define (at a low-level) what constitutes a trigger for the assessment state criteria. For example; consider the isolated assessment item of sustained or repetitive bending forward. There are 3 criteria "degrees" of the bending forward state:

0. Bending forward less than 20°
1. Bending forward >= 20 AND < 45°
2. Bending forward >= 45 AND 90°
3. Bending forward >= 90°

Sustained is defined as being held for 30 seconds or more continuously, repetitive is defined as being performed 3 or more times per minute.

Additionally, the assessment used by both the machine (auto) and human (ergo) in this project defines the required exposure ratings as:

0. Very rare:
   (< 30 minutes over the whole shift) OR
   (< 5 minutes at a time)
1. Rare:
   (>= 30 AND < 60 minutes over the whole shift) OR
   (>= 5 AND <15 minutes at a time)

[1] Coleman, Andrew (2006). Dictionary of Psychology (Second Edition). Oxford University Press. p. 688.

Ebbinghaus, Hermann (1913). On memory: A contribution to experimental psychology. New York: Teachers College.

https://en.wikipedia.org/wiki/Serial_position_effect - cite_ref-3 Deese and Kaufman (1957) Serial effects in recall of unorganized and sequentially organized verbal material, J Exp Psychol. 1957 Sep;54(3):180-7

Murdock, Bennet (1962). "Serial Position Effect of Free Recall" (PDF). Journal of Experimental Psychology.

https://en.wikipedia.org/wiki/Serial_position_effect#cite_note-Ebbinghaus-2

2. Unusual:
   (>= 60 AND < 90 minutes over the whole shift) OR
   (>= 15 AND < 30 minutes at a time)
3. Occasional:
   (>= 90 AND < 120 minutes over the whole shift) OR
   (>= 30 AND < 45 minutes at a time)
4. Frequently:
   (>= 120 AND < 240 minutes over the whole shift) OR
   (>= 45 AND < 60 minutes at a time)
5. Continuously:
   (>= 240 minutes over the whole shift) OR
   (>= 60 minutes at a time)

The system was identifying and tracking this state with high accuracy and consistency, as represented in in *Figure 1*. This example case uses 10 second time interval blocks for ease of visualisation (the system was sampling at 0.01 second blocks). The bend forward from time index 7 to 13 met the criteria for sustained (30 seconds or more), however the *degree* at which the bend would be tracked as was not defined.

After discussion and further definition of the risk assessment, the changes to the algorithms were implemented in preparation for the second on-site visit. Improvements to firmware and the Bluetooth programming library allowed the full five sensors to be used at once, compared to the four sensors for the first on-site visit.

Second onsite pilot (trial)

A second site visit at BMA's open cut coal mine, Peak Downs was conducted 17th - 18th May 2017. The aim was to gather data for subsequent verification through ergonomist task observation and assessment. Five maintenance tasks were observed and assessed:

- Filling blast/shot holes
    - Worker role: Shot operator/shothand
    - Department/Work area: BMA Drill and Blast Crew
- Changing bushes on Dragline electric motors – Dragline shutdown
    - Worker role: Electrician
    - Department/Work area: Maintenance
- Cleaning dragline – Dragline shutdown
    - Worker role: Cleaner
    - Department/Work area: Maintenance
- Replacing lower pins on dragline bucket
    - Worker role: Boilermaker
    - Department/Work area: Maintenance
- Cutting steel plate at ROM
    - Worker role: Boilermaker
    - Department/Work area: Maintenance

Sensors were attached to five males of different ages and body types. Sensors were attached to the back, hip, head and both wrists of the workers enabling assessment of discrete as well as combined movements such as simultaneous bending and twisting.

Second onsite pilot (trial) analysis

A primary objective for the second onsite test was to capture video (for ergonomic analysis) and gather sensor data for tasks of longer assessable and observable duration. This resulted in the majority (four of five) of the tasks analysed from the second onsite pilot trialling being from 12 to 18 minutes duration, and providing richer data than had previously been available. This permitted a comparison between the ergonomist and the automated system that had higher significant scoring.

Comparison between the sensor-detected states and the ergonomist analysed video footage of the tasks demonstrated close correlation; the automated system is following the risk assessment criteria precisely to generate the risk score. However, the risk-scores derived respectively from the automated assessment and the ergonomist assessment can differ in magnitude (see Tables 1-5), with the automated assessment generally scoring the same task slightly higher than the ergonomist. In each of four cases, both the auto and the ergo risk scores were in the same band i.e. delivered the same risk level descriptor and recommendation used in the Risk Score Guidelines shown in table 6.

An exception to agreement between the auto and ergo assessment was with respect to the filling blast shot holes task (Table 4). In this instance, the ergo score of the task was substantially higher than the auto score. The task involved the worker being stationary while swinging his arms for an extended period. The arm swing was similar to that usually associated with walking but in this case, was used to move a rope. The ergo scored the action based on it being a repetitious action for an extended period (score 100) while the auto scored the action based on it being similar to walking (score 0) i.e. the main contributor to the difference in scores is the limb & joints movements per minute category (D6h).

Having identified this discrepancy, the machine learning algorithm can be used to enable the auto system to use the absence of movements detected by the other sensors to detect non-walking activities. This will be developed during the extended post-project trials.

The existing risk assessment protocol is fundamentally based around the task in context of the work shift. As the tasks observed were specific, discreet tasks, with their frequency of occurrence throughout a person's shift unknown, both the scores from the automated system and the ergonomist were normalised to a 1 hour shift for comparison purposes. In the sense that the scores generated are risk score per hour of the task.

The ergo observation and analysis of the video footage demonstrated that ergonomist judgements of severity and significance increase as the volume of data increases. Simply put, humans are expert at dealing with a multitude of inputs by filtering to enable cognitive processing of what experience and training signify as important. This is particularly so in relation to the analysis of observed multiple repetitive and sustained actions over longer durations.

The automated system does not analyse data in the context of other tasks that it has analysed; instead it objectively analyses data input for each discrete task. While the criteria of the risk assessment methods are the same, the automated system feeds-forward into the risk assessment to obtain a risk score, whereas the ergonomist would appear to feed-back into the risk assessment to convey a risk score.

This may reveal a limitation of the automated system using risk assessment criteria and weighting designed for use by a human ergonomist. Further research would be needed to determine adjusted criteria and weighting for the automated system to use to produce risk-scores that are directly comparable to ergonomist risk scores. However, the automated system is consistent with itself between various tasks, which would seem to indicate that it can determine the level of risk and compare the level of risk for work activities, provided that the existing risk assessment criteria are comparable.

Further work in this area will require the employment of a panel of ergonomists to increase the reliability of the human comparisons with the automated system and provide sufficient data to test the statistical significance of any discrepancy between the respective analyses.

Assessment Category	Automated	Ergonomist
Repetitive or sustained	91	74
Heavy loads or high forces	0	2.5
Difficult or awkward loads	-	0
Vibration	0	0
Occupational overuse syndrome	-	5
Total	91 (substantial)	81.5 (substantial)

Table 1: Cleaning dragline risk assessment

Assessment Category	Automated	Ergonomist
Repetitive or sustained	59.5	45
Heavy loads or high forces	10.0	16.5
Difficult or awkward loads	-	2.5
Vibration	0	0
Occupational overuse syndrome	-	0
Total	92 (substantial)	64 (possible)

Table 2: Cutting steel plate risk assessment

Assessment Category	Automated	Ergonomist
Repetitive or sustained	52.5	35.0
Heavy loads or high forces	25	24.5
Difficult or awkward loads	-	0
Vibration	0	0
Occupational overuse syndrome	-	8.0
Total	77.5 (substantial)	67.5 (possible)

Table 3: Replacing dragline bucket pins risk assessment

Assessment Category	Automated	Ergonomist
Repetitive or sustained	36.5	149.5
Heavy loads or high forces	7.5	2
Difficult or awkward loads	-	0
Vibration	0	0
Occupational overuse syndrome	-	0
Total	44.0 (possible)	151.5 (substantial)

Table 4: Filling blast shot holes risk assessment

Assessment Category	Automated	Ergonomist
Repetitive or sustained	50	41
Heavy loads or high forces	-	3.5
Difficult or awkward loads	-	7.5
Vibration	-	0
Occupational overuse syndrome	-	0
Total	50 (possible)	52 (possible)

Table 5: Changing bushes risk assessment

Risk Score	Recommendation
> 400	Very High Risk; Discontinue Operation
200 - 400	High Risk; Immediate Correction Required
70 - 200	Substantial Risk; Correction Needed
20 - 70	Possible Risk; Attention Indicated
< 20	Risk; Perhaps Acceptable

Table 6: Risk score guidelines

Development of the user interface with the app has continued throughout the project and the site trials have found the operation to be intuitive, enable simple presentation of risk assessment data and it facilitates discussion with site personnel. Task management, cloud syncing of data, and the systems for simultaneous video recording (at the same time as the sensor data were developed and implemented.

Conclusion

An automated musculoskeletal injury risk assessment system that employs wearable sensors paired with an app has been successfully developed. The app works on phones and tablets using a developed machine learning system to analyse data and present it on intuitive screens in simple report formats.

The risk assessment method employed by the application is based on and is closely aligned to the Australian Model Code of Practice - Hazardous Manual Tasks 2016 and its predecessor codes, guides and national standard. This method has been extended to address a factor that limits application by both expert and casual users; the consequence scoring in the risk estimation calculation has been populated using extensive injury clinical and claims data. This standardised method results in the provision of ranked scores based on type of injury risk and enables use alongside other Work Health & Safety risk-scoring.

The risk assessment process was verified by human expert (ergonomist) observation and assessment of the manual handling tasks being app-assessed. Comparison between the sensor-detected states and the ergonomist analysed video footage of the tasks demonstrated close correlation; the automated system is following the risk assessment criteria precisely to generate the risk score and therefore brings a high degree of reliability to the assessment process.

The risk-scores derived respectively from the automated assessment and the ergonomist assessment can differ in magnitude but over the limited trials completed, the ergo and app risk scores were in the same band i.e. delivered the same risk level descriptor and recommendation. An exception to this was a specific task that was assessed where the subject was stationary while swinging his arms for an extended period and the two assessments disagreed. Having identified this discrepancy, the machine learning algorithm can be modified and developed during the extended post-project trials.

Two issues have been identified with the human versus automated system assessments; 1. The human assessment is subjective and while using the Australian Model Code of Practice assessment process the human introduces many assumptions and a degree of bias based on knowledge of the task. This means the reliability of the human assessment is lower than that of the app and in any given assessment there may be disagreement between the app and human-calculated risk score; and 2. The computing rate of the app makes it better able to quantify repetitious movement than the human.

Further work is required to assess the ways in which subjectivity is introduced into the human use of the Australian Model Code of Practice risk phrases and how this may be addressed within the app.

(vii) Technology Transfer Activities

The outcome of this project is an app that pairs with wearable sensors to enable automated MSD risk assessments. The intellectual property (IP) rests in the software and algorithms within the application.

Successful evaluation through the extended industry trials will be followed by commercialisation. This will involve the production of product packages and marketing to the coal mining industry nationally, the metalliferous sector nationally, the international market and other industries. Product packages shall include the application and sensors, support and training. The electronic components of the package will be SIMTARS certified for underground use.

There will be presentations to industry conferences, seminars, trade shows, publications, etc. for promotion and marketing purposes.

During the trial stage of the project commercial partnering will be sought to enable production, route to market and end user support on a commercial scale. Planning and investigation of potential partners has commenced.

(viii) Acknowledgments

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