Hand Motion Recognition of Shipyard Welder Using 9-DOF Inertial Measurement Unit and Multi Layer Perceptron Approach

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Abstract. A viable system that can monitor the effective working time of welder in real-time is required to overcome the low use of effective welder time in the Shipbuilding Project in the Indonesian Shipyard. It is made possible by using a wearable sensor tri-axial accelerometer, gyroscope, and magnetometer. In this research, sensors are used to recognize typically hand motion of welder during welding activities: preparation, welding and cleaning slags, respectively in three welding positions 1G, 2G, and 3G. Initially, observations were made to recognize the relationship between welder activities and hand motion. Second, raw data containing hand movements from the welder is captured in the form of time-series signals using inertia sensors for various different activities. Third, the raw data of measurements for those activities is extracted and analyzed to identify significant features such as mean, root-mean-square, power spectral density using the welch method (autocorrelation, spectral peak, and spectral power). Finally, typical activities of welder are classified using the resulting feature data with Multi Layer Perceptron. The validation of results shows that the algorithm is capable to recognize the hand motion activities of the welder.

1. Introduction

Delay in ship construction activities contributed to the delay in new shipbuilding projects in Indonesian shipyards [1]. This activity can be divided into 4 steps, namely fabrication, sub-assembly, assembly, and erection, wherein the sub-assembly, assembly, and erection, welding is substantial process. The most widely used welding process is still manual shielded metal arc welding (SMAW). This process is still executed manually by a welder using hand motion and the quality of weldment is dependent mainly on the skill of a welder when manipulating the hand motion by reference to the appropriate welding procedure specification (WPS)[2]. The workers' performance is one of the factors that gives a delay effect on the project, such as attitude and discipline [3]. One example is several welders only use 4 effective hours from 8 hours available every day. It is therefore shipbuilding process require a better monitoring approach of human performance based on real time monitoring.

The research of the monitoring system in civil construction now has used the application of the motion analysis system (MAS). MAS becomes a valuable system for manufacturing or workstation to improve productivity and ergonomics aspects [4]. Now, MAS for construction workers has been
developed using wearable sensors [5]. The monitoring process is executed by identifying the worker's posture in the practice of construction using supervised learning techniques [6]. Such sensors and applications commonly used have been reported in several studies below.

The accelerometer sensor using data from smartphones was reported in [7]–[9], or from wearable devices [10]–[13]. An accelerometer can be used also to track user position shifts by integrating twice the acceleration data [10]. Besides that, acceleration data can also be used to classify the activities of its users. Frequently approach that used is the Support Vector Machine (SVM) model [13]–[15] and the Multi-Layer Perceptron model [9], [14]. Acceleration data can also be classified using deep learning with the Deep Convolutional Neural Networks model [16] and with the development of cloud infrastructure [17], the other approach is using the Long Short Term Memory (LSTM) Model-based feature extraction [18], and using the Recurrent Neural Network (RNN) Model [19]. The classification process can also be carried out by combining accelerometer with gyroscope measurement data [16], [17], [19] and in combination with magnetic field data measured by a magnetometer [10]. The use of electrocardiograms (ECGs) is explained in ref. [20], and the use of a passive infrared sensor (PIR sensor) is identified in ref [21]. Experiments using these sensors have been used to recognize human activities during medical care in a hospital, such as falling, moving, sleeping, and walking.

However, the use of such inertial sensors for real-time monitoring of shipyard workers especially the welder is still limited. In this research conducted a study on hand motion recognition system of shipyard welder using three-axis wearable sensors: accelerometer, gyroscope and magnetometer and Multi Layer Perceptron (MLP).

2. Literature Review

2.1. Hand motion of manual arc welding

Manual arc welding can be defined as ”welding with a gun, torch or holder and controlled by hand”. Welder executes the welding function and maintains continuous control of the welding operation by hand [22]. Therefore, manual welding requires significant skill and dexterity in order to achieve good quality weldment [23]. During the process, electrodes are melting into the weld pool and becoming shorter. At the same time, a welder should keep maintaining a constant arc distance and electrode combustion rate. A skilled welder has the capability to maintain a constant hand for manipulating the electrode, and appropriate training of welders is necessary in order to achieve satisfactory welds. The capability of a skilled welder in maintaining various types of hand motion continuously when manipulating electrodes to weld in 1G, 2G and 3G position is figured out in Figure 1.

![Figure 1. Electrode manipulation motion at; (a) 1G, (b) 2G, (c) 3G](image-url)
Hand motion of a welder is basically very typical and characterized by various actions such as weaving, dragging and pushing which then forming the typical gesture of a welder. Some patterns of "weaving" have been implemented to produce good weld beads. Strike beads are a straightforward bead in which "pulling" or pushing the torch across the joint with minimal side-to-side movement. Pulling means the electrode is pointing back towards the weld pool, leading it. This enables maximum penetration and a robust-looking weld. when welding thin metals or thick metal with vertical-up position (3G-Position), "pushing" the torch means pointing the electrode forward.

Strike beads generally not very wide can be used in any welding position. Weave beads are used for wider welds. There are various types of weaves, such as zig-zag and crescent technique and many others. Besides allowing a wider bead, weaving is applied to control the heat in the weld pool. Besides that, it is sometimes required to pause on each side of the weld to achieve a good tie in and avoid undercutting from the edges. When welder moves across the center of the joint, sometimes rushing act is needed. Otherwise, this may end up with a high crown. It's preferred to have a slightly convex weld face when you weave.

In vertical-up welding, this weave technique allows you to compose a sort of shelf behind the weld pool, keeping the molten metal from sliding downward. To keep the weld pool from overheating or expanding, the welder can do a semi-circle weave, with the center point or your stroke crossing the front of the weld pool. If welder needs more heat in the weld pool, weave back through the weld pool.

It can be summarized that the motion of the hand welder explained above consists of linear acceleration combined with angular acceleration. Such a typical movement can be monitored and recorded using sensors of accelerometer and gyroscope located on the active welder wrist during the welding process as seen in Figure 2.

![Figure 2. Typical hand motion of manual arc welding](image)

2.2. Human Motion Study

Human motion is the body or a part of body movements that involve changes in a person's position or posture relative to his environment [24]. Various elements of human motion basically consist of biomechanics and kinesiology as seen in Figure 3 [25]. This research focuses on the use of kinematics sensors.

It is known that studies used in analyzing human movements are biomechanics and kinesiology studies as seen in Figure 3. Kinesiology studies emphasize the anatomical and physiological functions of a movement, whereas biomechanical studies emphasize the knowledge and mechanical methods applied to these movements [26]. From biomechanical studies, motion can be divided into 2, namely kinematics and kinetics. Kinematic motion only focuses on the characteristics of motion without reference to the forces that cause motion. Therefore the data used in kinematics analysis include
position, velocity, acceleration data both in linear motion and in angular motion [26]. While motion kinetics is more focused on the cause of motion [26].

![Classification of Human Motion Analysis](image)

**Figure 3.** Classification of Human Motion Analysis [25]

Several studies on motion studies have been developed for monitoring the human condition. Among them, measurements of the physical intensity of a construction worker [27], the fatigue of a construction worker's body [28], to monitor the physiological status and activity in a construction work environment [21].

### 2.3. Human Activities Recognition

Nowadays, Human Activity Monitoring has begun to be used in a wide area. Equipment that is often used in monitoring activities are cameras, PIR sensors, and Wearable Motion Sensors such as accelerometer, gyroscope, magnetometer, GPS, etc. [18], [29]–[34]. Most of the research that has been done is still examining the general activities carried out by humans such as walking, sleeping, standing, climbing stairs, and going downstairs. Nevertheless, no such system is indicated to be implemented in more complex working activities such as welding.

The three main processes of identifying activities using wearable sensors are sensor location, data pre-processing, and data classification. First, the inertia sensors are located in a part of the body so that when monitoring the activity carried out, sensor data can monitor and record each activity. [21] studied the reliability and usability of wearable sensors for monitoring roofing workers' on-duty and off-duty activities, more specific heart rate, energy expenditure, metabolic equivalents, and sleep efficiency.

The second is the pre-processing of raw data. These activities include data segmentation and data feature extraction [35]. Pre-processing data is a method for finding typical characteristics for several activities, called feature. The main difference between the two approaches is the way the feature is extracted, that is, whether it is extracted manually or automatically [8]. This difference is highlighted because the feature extraction common process is frequently limited by human knowledge [36]. The feature extraction process is carried out in two main domains: time domain and frequency domain [37]. Several features are commonly extracted from the raw data as adopted from various studies of signal processing created by sensors as can be seen in Table 1.

| features             | definition                                      | ref.     |
|----------------------|-------------------------------------------------|----------|
| mean root mean square (RMS) autocorrelation | height of the main peak; height and position of the second peak | [39]     |
| spectral peaks       | height and position of first 6 peaks             | [39], [40] |
| spectral power       | total power in 5 adjacent and pre-defined frequency band | [39]     |
|                      |                                                 |          |
The features number used in the dataset will have an impact on the costs of data processing and the accuracy of the classification models generated during the learning phase [41]. In this case, the process of reducing the dimensions of the data by removing irrelevant features to improve the accuracy of the classification model is required. The importance of feature selection is emphasized more significantly than those selecting classification algorithms. This is because poor feature quality or inappropriate feature selection can affect the accuracy of any model produced by conventional machine learning algorithms [42].

The third is the classification process using features data in the machine learning process. One of the classification methods in machine learning is the Multi Layer Perceptron. Multi-Layer Perceptron is one of the most commonly used Neural Network architecture due to its lower complexity and ability to produce a satisfactory result for non-linear relationships. This network is trained using supervised learning. A MLP usually consists of three or more layers: an input layer, one or more hidden layers and an output layer [43]. The general structure of MLP is presented in Figure 4.

The most significant elements of MLP are the connection weights and biases. The output of each node is calculated in two steps [44]. In the first step, the weighted summation of the input is calculated using the equation:

\[ S_j = \sum_{i=1}^{n} w_{ij}I_i + \beta_j \]

where \( I_i \) is the input variable, \( w_{ij} \) is the connection weight between \( I_i \) and hidden neuron \( j \), \( \beta_j \) is bias. In the second step, an activation function is used to generate the output of neurons based on the calculated weighted summation value. Different types of activation functions such as Logistic, Hyperbolic, Exponential, and Sigmoid can be used in MLP.

MLP is trained using Supervised Method. The classification performance of NN depends on the selection of learning algorithms. In general learning, methods are mainly classified into Gradient-based and Meta-heuristic search methods [45].

Training of MLP using Back Propagation algorithm includes two phases: Propagation and Updation of weights. In first phase the information presented in input vector is propagated forward through the layers of the network. The error values between actual output and desired output is evaluated and these errors are propagated backwards. Gradient value is calculated using these error values. In second phase the weights are updated by the optimization of the calculated gradient. Optimization is the process to achieve the best outcome of a given operation while satisfying certain conditions. The training process will be continued until maximum number of epochs or the minimum acceptable error reached. After completion of the training process, testing on another set of inputs will be done to determine how well Back Propagation generalized on the untrained inputs. The
performance is evaluated generally using the measures such as Mean Squared Error (MSE) or Root Mean Squared Error (RMSE).

Different types of Back Propagation algorithms can be applied to train MLP network. In this section the theoretical background of widely used training algorithms such as Levenberg-Marquardt, Quasi-Newton, Resilient Back Propagation, Conjugate gradient and Gradient descent with variable learning rate are presented [46].

3. Research Methodology

First, observation of welder activity and interview about the scope of work was conducted. As a result, the scope of work of welder activity consists of welding tools preparation, welding joint check, welding execution, slag cleaning, and repairing reject weldment. These activities are commonly conducted by a welder in all welding positions.

Second, developing measurement and recording tools using inertia sensors consisting of a three-axis accelerometer and gyroscope. The first tools developed were used Arduino as microcontroller and MPU 6050 six-axis sensors. Due to memory limitations, the Arduino microcontroller is then replaced using the Raspberry-Pi microcontroller. However, the Raspberry-Pi based sensors have a limitation due to lost connection of data cabling to sensors frequently occur. Finally, this research was executed using MetaMotion Sensors.

MetaMotion sensors is a sophisticated product developed by Mbientlab.inc. using a Bluetooth connection and complete with software to connect with a smartphone, raspberry, and computer functioning as the controller. In this research, the tools used to record welding activity experiments in the laboratory are the MetaMotion sensor and smartphone. Materials prepared is a steel plate specimens and welding wire. Tools that are prepared are welding machines, glove, welding hood, grinding machine, welding hammer, wire brush, clamp, meta motion sensors, and a smartphone.

Third, the experiment for recording training data of hand motion was executed. Welder activities recorded include preparation, welding, and cleaning slag activities in 1G, 2G, and 3G positions subsequently. Such experiments are repeated for different subjects to obtain diversity in motion data. The results of the experiment are raw data and time records of each activity.

Figure 5. Step for analysis and developing recognition techniques
Fourth, analysis of the data and developing recognition techniques using the MLP. Analysis process can be seen in Figure 5. In data pre-processing, raw data was divided and grouped every 30 seconds which is called window data. Each window data was then extracted according to several features as commonly used in the signal processing analysis. Furthermore, the featured data are then prepared and labeled as a training data set and testing data set. The training data set are used to develop the Multi Layer Perceptron supervised learning algorithm.

4. Result

4.1. Shipyard Observation Results
Observations were made of six welders working at the shipyard in the process of building a new ship. In addition, some interviews were conducted with supervisors controlling the shipyard welder. It can be concluded that the activities carried out by a welder broadly include: a) preparing welding equipment, b) reviewing welding procedure specifications (WPS), c) checking weld joints, d) preparing weld joints, e) using personal safety equipment, f) welding execution, g) cleaning slag, and h) repairing rejected welds. Some welding positions generally carried out by shipyard welder are 1G (down hand), 2G (horizontal) and 3G (vertical up) can be seen in Figure 6.

Welding activities in real shipyard situations are often very different from those carried out during welder qualification tests (as seen in Figure 6). The posture of the welders sometimes is restricted by a construction depending on the position of the weld joint to be worked on. In this study, experiments are conducted in laboratories with conditions similar to the situation when a welder qualification test is performed. However, the dominant body part monitored in the welding activity remains the wrist.

![Figure 6. Various welding position in shipyard: (a) 1G, (b) 2G, and (c) 3G](image1)

**Laboratory Experiment Results**
Experiments in the laboratory were carried out in the welding position of 1G, 2G, and 3G as shown in Figure 7.

![Figure 7. Experiments in the laboratory: position (a) 1G, (b) 2G, dan (c) 3G](image2)
It is known that the sensors located at the wrist of a welder can continuously record the measurements of the magnetic field using a magnetometer during various activities in μT. A graph showing those measurements can be seen in Figure 8.

**Figure 8. Magnetic field graph for various activities (in μT)**

The measurements are grouped according to three activities: preparatory activities (number 1), welding execution (number 2), and slag cleaning (number 3). The magnetometer values on the X-axis are marked in blue, Y-axis is indicated in yellow, and Z is marked in red. Based on these graphs, it is known that the measurement value of the magnetic field in the welding execution tends to be greater than those in the slag cleaning and preparation activity. This is caused by the different magnitude of electric source applied during those activities [47].

Further observation shows that the magnitude of linear acceleration is varied in each activity as figured out in Figure 9.

**Figure 9. Linear acceleration graph for various activities (in g)**
As seen in Figure 9, it is shown that slag cleaning activity (activity 3) affects the highest variation in the linear acceleration. While in the welding activity (activity 2), the variation of the linear acceleration measurements tends to be low and stable. This condition is required as during welding activities, travel speed must be maintained at a certain level to meet the requirement according to welding procedure specification (WPS) and to obtain a good quality of weldment.

The result of angular acceleration measurements shows also different characteristics of the three activities in each activity as depicted in Figure 10.

![Angular acceleration graph for various activities (in °/s)](image)

Figure 10. Angular acceleration graph for various activities (in °/s)

Figure 10 shows that the largest variation of angular acceleration was indicated in the slag cleaning activity. While the lowest variation of angular acceleration occurred during the welding activity. After evaluating the results of many measurements data, it can be concluded that generally, signal characteristics measured by the three sensors accelerometer, gyroscope, and magnetometer tend to be similar or indicating low variation for the three welding positions of 1G, 2G, and 3G.

When motion of welding position, there are Changes in the position of hand motion on the X, Y, and Z-axis direction. In the 1G position welding activity, changes in the position of the hand only occur on the X and Z axis, while for small changes indicated on the Y. In the 2G position welding activity, changes in position on the hand only occur on the X and Y axes, while slight changes occur on the Z-axis. In the 3G position welding activity, changes in position on the hand only occur on the Y and Z axes, while slight changes occur on the X-axis.

4.2. Classification of Measurement Data

Data from laboratory experiments are divided into several window data with a duration of 30 seconds each called subset data. Subset data is normalized with a high pass filter to removing gravity. Then, labels for each activity class are given as follows: (1) welding 1G, (2) welding 2G, (3) welding 3G, (4) cleaning slag 1G, (5) cleaning slag 2G, (6) cleaning slag 3G, and (7) preparing to weld. Each subset of data is extracted to find the specific characteristics of time-frequency based signal processing. these characteristics include mean, root-mean-square (RMS), and power spectral density. The feature extraction table is then used as training data and test data to develop a welding activity recognition system using MLP Supervised Learning algorithm.
4.3. Welding Activity Recognition

The experiments were started with various types of MLP approach. Every various type of MLP have 5 hidden layer with Experiments were carried out using the learner classification tools in Matlab software for student version license to the ITS (Sepuluh Nopember Institute of Technology, Surabaya). The test was carried out using several MLP and the results can be seen in Table 2.

| No | Various of MLP                                      | Log-Sigmoid | Linear | Hyperbolic tan - sigmoid |
|----|----------------------------------------------------|-------------|--------|--------------------------|
| 1  | Levenberg-Marquardt                               | 0.96941     | 0.80439| 0.98377                  |
| 2  | BFGS Quasi-Newton                                  | 0.49913     | 0.69361| 0.89982                  |
| 3  | Resilient Backpropagation                          | 0.94203     | 0.96548| 0.86315                  |
| 4  | Scaled Conjugate Gradient                          | 0.92150     | 0.65774| 0.93277                  |
| 5  | Conjugate Gradient with Powell/Beale Restarts      | 0.73578     | 0.86123| 0.40196                  |
| 6  | Fletcher-Powell Conjugate Gradient                 | 0.39188     | 0.48070| 0.09577                  |
| 7  | Polak-Ribiére Conjugate Gradient                   | 0.69376     | 0.42996| 0.68028                  |
| 8  | One Step Secant                                    | 0.83905     | 0.40212| 0.92265                  |
| 9  | Variable Learning Rate Backpropagation             | 0.29511     | 0.75178| 0.93788                  |

Experiments using Matlab software shows that training with Levenberg-Marquardt MLP technique can correctly predict up to 0.989377 with hyperbolic tan sigmoid transfer function. This MLP structure used in this study can be seen in Figure 11.

![Figure 11. Levenberg-Marquardt MLP Structure](image)

The results of training using the Levenberg-Marquardt variation indicate the level of performance, training state, and regression values as shown in Figure 12.

![Figure 12. Graphic for (a) performance, (b) training state, and (c) regression values](image)

The training, validation, and testing process is then performed using the leverberg-marquardt multilayer perceptron approach. the results showed the overall predictive ability of the 97 percent was reached as can be seen in the confusion matrix showing in Figure 13.
5. Discussion and Conclusion

The main purpose of this work is to develop a robust hand welder activity recognition system using data from three types of wearable sensors: accelerometer, gyroscope & magnetometer. It seems very feasible to use such wearable sensors for hand welder activity recognition. It is similar to the smartwatch as one of the most used devices by people in their daily life, not only for communicating with each other but also for a very wide range of applications, including healthcare. Thus, a novel approach has been proposed here for activity recognition using wearable inertial sensors consisting of accelerometers, gyroscope and magnetometer sensors. It was observed from the experiment that the motion of hand welder consisting of linear acceleration combined with angular acceleration can be monitored using an accelerometer and gyroscope accordingly. While the real welding activity can be monitored using a magnetometer as the active electric source affect the generation of magnetic force.

From the sensor measurement signals, multiple robust features of signals have been extracted to be mean, root-mean-square, spectral peak, autocorrelation, spectral power followed by data normalization and labeling. Furthermore, the features have been processed with Levenberg-Marquardt MLP technique for activity training and recognition. Training results using the Levernberg-Marquardt variation show high accuracy rate. In Figure 13, there is a NaN% value which indicates no value. This shows that there are still activities that are not tested or tested. this is because the data used for the test process is sampled by random methods.

The proposed system of welder activity recognition provides considerable benefits such as the minimal involvement of job inspector, non-contact supervision as well as real-time and in-process monitoring of welder’s productivity. Implementation of the proposed system in a real situation will be more effective to increase the productivity of welders if combined with the implementation of activity-based salary systems.
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