A
nalysis of Wrist Hand Motion for Monitoring of Basic 
Welder Training using Wearable Sensors 

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Abstract. During the training of a welder, either novice or professional, most activities are focused on the acquisition of wrist-hand motion skills. In the basic welding training, trainees initially required hand-on practices to acquire the skills of wrist hand motion to maintain the distance of electrode tip to a base metal such that the welding arc was continuously flaming. Secondly, trainees were practices of manipulating hand motion to follow seam tracking for joining two metals within defined speed & torch height. These practices were then continued for various types of weld joints. The result of acquiring this skill level was then assessed by inspecting the visual appearance of the weldment. In this study, an effort was undertaken to monitor and assess the progress of acquiring wrist-hand motion skills using wearable sensors: accelerometer, gyroscope, and magnetometer. Then, the record of those sensors was plotted as a time series signal compared with those performed by the training instructor. Their achievement of skills grade was analyzed using the Supervised Vector Machine (SVM) Learning Method. The result has indicated that this proposed method can assist in assessing welder trainees' efforts to improve their skills. 

Keyword: Wrist Hand Motion, Wearable Sensors, Training, Welding 

1. Introduction 

The development of welding technology has been directed to robotics to overcome the scarcity of welders in modern industrial countries [1]. Many researches have been carried out to replace the skills of welders with robots. In addition, efforts have extensively been undertaken to develop welding simulation equipment to make people more convenient and comfortable for learning and practicing the welding skills, including those developed based on virtual reality (VR) or augmented reality (AR) technology [2]. However, either the implementation of robot technology or the welding simulation is presently still considered too expensive, especially in developed countries with sufficient availability of people are willing to become skilled welders. 

To obtain skilled welders is necessary to train them following Welder Procedure Qualification (WPQ) approved by an authorized institutions such as the Indonesian Classification Bureau (BKI) or other Classification Beureaus [3]. Welders need to experience hands-on skills and to know basic knowledge of welding techniques. There are various certificates in welder certification, namely based on base metal types, the types of the welding process, and the welding position as specified in
Welding Procedure Specification (WPS). Qualification tests are also required before the welders perform a welding job with a different WPS [4].

In many cases, welder trainees often feel that they already have the welder skills according to the specific WPS because they have previously had a welder's certificate. However, if a different WPS is applied, they are still necessary to pass an assessment for the qualification test. This requires costs of base metal materials, electrodes, welding machine rental fees, non-destructive tests, and destructive tests that are expensive enough. Currently, the assessment system to determine the welder skills grade is still using conventional methods. The instructor evaluated the trainees based on the visual inspection of welding results and continued with a destructive and non-destructive test.

It has been observed that the acquisition of wrist hand motion skills was one of the main significant parameters to become a professional and qualified welder. However, no method has been indicated to implement real-time monitoring of welding skill acquisition based on the wrist-hand motion. The present availability of wearable sensors, the internet of things (IoT), and artificial intelligence (AI) technology make it possible to realize such a real-time monitoring system.

The purpose of this work was to study the possibility of applying wearable sensors technology to monitor and to assess basic welding trainees based on their skills performing the appropriate wrist-hand motion of welding, including analyses of the resulting time series signal graph using the Support Vector Machine (SVM) method. The proposed real-time monitoring and assessment might be performed more systematically and cost-efficient.

2. Literature Review

2.1. Welding

A welding process has been defined as the process of joining materials or non-metals that produce a fused part by heating the material to be bound to a specific welding temperature, with or without emphasis, and with or without filler metal. Welding occurs because the metallurgical bond in the alloy is carried out in a liquid state and then solidifies [4].

Welding activities were classified based on the type of process, such as Shielded Metal Arc Welding (SMAW), Gas Metal Arc Welding (GMAW), Gas Tungsten Arc Welding (GTAW), and Flux Core Arc Welding (FCAW). This study focused on the SMAW, a metal joining process that uses heat energy to melt the workpiece and electrodes (fill material). The SMAW welding process produces heat energy from the electric ion jumps (cathode and anode) occurring between the electrode tip and base metal.

Welding position is setting the position of the welding electrode movement by reference to the position of base metals. Two characters indicate the position and type of welding joint performed. The first character uses the number as follows: flat position indicates by number 1, horizontal position indicates by number 2, and vertical position indicates by number 3. The second character indicates a type of welding joint, in which F indicates a fillet joint, and G indicates a groove joint.

2.2. Types of Welding Defects and Causes

Welding defects are welding results that do not meet the requirements according to the standard such as published by the American Welding Societies (AWS). Welding defects are still tolerated if the amount does not exceed 25% of the total surface area of the material [5]. Discontinuities in welding usually occur because the welder is not properly maintaining his hand movements during the welding process.

In this case, the instructor has guided to determine the welding parameters, and the trainees' task was to train their hand movements so that they were continuously stable to minimize welding defects. There are several types of welding defects and their causes according to the AWS.

1. Undercut (U) is a defect on the surface or root; this defect is like an overdraft in the base metal or parent metal. Undercut occurs because the welding speed is too high, especially at the edges of the welding.
2. Porosity (P) is a defect in the form of a small hole in the weld metal (welding metal), which can be on the surface or inside.

3. Incomplete Penetration (IP) is a defect occurring at the root area of a weldment. It is considered to the IP if the welding in the root area does not penetrate or the reinforcement in the weld root is concave. These defects are caused by the position of the electrode, which is not properly inserted and is caused by too high welding speed.

4. Incomplete Fusion (IF) is an unwanted welding result due to imperfections in the joining process between the weld metal and the base metal [6]. This type of welding defect is due to the high welding speed.

5. Root Concavity Defect is imperfect welding result in root area or concave penetration welding result.

6. Overlap defect occurs on the surface and roots because the weldment exceeds the weld seam, and filler metal does not melt with the base metal.

2.3. Basic Welding Training

Basic welding training was aimed for undergraduate students who did not have welding skills and learned to weld firstly. In this training program, a trainee was trained to practice turning on the welding arc. They focused on acquiring skills of wrist-hand motion to move electrode and its holder straightly, at a certain welding speed, with the right electrode angle and the correct arc length height according to the guidance of the instructor, who usually following the defined WPS. Various weaving techniques were also needed to practice maintaining the consistency of appropriate wrist-hand movements. The holder with electrode and electric cable itself had considerable weight and required special exercises and endurance for moving it in a relatively long time while maintaining the proper hand motions. The syllabus of basic welding training examined in this study can be seen in Table 1.

**Table 1. Example syllabus of basic welding training**

| Type of Welding                  | Welding Position Image | Existing Hand Motion |
|---------------------------------|------------------------|----------------------|
| Straight                        | ![Image](image1.png)   | ![Image](image2.png) |
| Weaving                         | ![Image](image3.png)   | ![Image](image4.png) |
| 1F (Flat Position and Fillet Joint) | ![Image](image5.png)   | ![Image](image6.png) |

The syllabus of basic welding training was a part of the undergraduate course of the Department of Naval Architecture of Sepuluh Nopember Institute of Technology (ITS) Surabaya, Indonesia,
containing the type of specimen used and welding position and hand-on practices of wrist-hand motions. The trainees must experience skill practices of maintaining proper wrist-hand motions during the welding process within considerable time and tried to minimize welding defects during the welding process.

2.4. Wearable Sensors

Wearable Sensors are sensors that can be mounted on the human body and implemented in everyday life based on their aesthetics and function [7]. The sensors frequently used are an accelerometer to monitor and measure the linear acceleration of an object, a gyroscope to track a device's rotation or rotation based on the motion, and a magnetometer [8] which functions to monitor the vectors of a magnetic field [9]. The wearable sensors can also be interpreted as devices that can be used on parts of the human body related to computer devices and the latest internet of things (IoT) technology [10]. A study on the identification of welding activities with MetaMotion sensors by MbientLab has shown that welding activities could be recognized with fairly good accuracy [11]. In this study, a MetaMotion wearable device by Mbientlab was used [12] those specifications are described in Table 2.

| No | Sensors      | Specification                                      |
|----|--------------|----------------------------------------------------|
| 1  | Gyroscope    | Range: ± 125, ± 250, ± 500, ± 1000, ± 2000°/s    |
|    |              | Resolution: 16 bit                                 |
|    |              | Sample Rate: 0.001Hz – 100Hz stream – 800Hz log   |
| 2  | Accelerometer| Range: ± 2, ± 4, ± 8, ± 16 g                      |
|    |              | Resolution: 16bit                                  |
|    |              | Sample Rate: 0.001Hz – 100Hz stream – 800Hz log   |
| 3  | Magnetometer | Range: ±1300μT (x,y-axis), ±2500μT (z-axis)       |
|    |              | Resolution: 0.3μT                                  |
|    |              | Sample Rate: 0.001Hz – 25Hz                        |

2.5. Machine Learning and Feature Extraction

Machine Learning (ML) is one of the Artificial Intelligence (AI) techniques for predictive modeling that relies on computers to study complex linear and non-linear interactions. This technique works by minimizing the errors between the input prediction and targeted output using supervised learning algorithms [13]. Machine Learning has been divided into two, namely shallow learning algorithms where extraction is done manually and deep learning algorithms where extraction is done automatically. Both had differences from the conventional processes, which were limited by human knowledge [14]. In the feature extraction process, the statistical analysis of the time signal graph used the features that are listed in Table 3 [15].

| features           | definition                                      |
|--------------------|-------------------------------------------------|
| mean               | average of a data set [16]                      |
| root mean square (RMS) | the square root of the mean square [16]         |
| autocorrelation     | height of the main peak; height and position of the second peak [17] |
| spectral peaks      | height and position of first six peaks [17], [18] |
| spectral power      | total power in 5 adjacent and pre-defined frequency bands [17] |

3. Methodology

3.1. Research Method

The experiment carried out in this study was focused on monitoring and evaluating the trainees' skill acquisition of wrist-hand motion during the basic welding training course. In this study, the parameters of the qualified WPS are used as a reference and illustrated in Figure 1.
Figure 1. Illustration of the fixed parameters and the parameters studied in the experiment

Figure 1 illustrates fixed parameters and observed parameters in this study, derived from the qualified WPS (Welding Procedure Specification). The observed parameters in the yellow box are the welding parameters affected by the welder's wrist-hand motions. At the same time, the fixed parameters in the grey box are defined according to the specified WPS.

Following the WPS, trainees must know and do practices to maintain several observed parameters and consistency of wrist-hand movements during training to produce good weldments. Trainees were expected to achieve and maintain a consistent welding speed, welding weaving, electrode angle, setting the torch height distance, and pushing and dragging the electrode correctly and continuously moving their wrist-hand during the welding process.

3.2. Experimental Equipment
Several types of equipment used and data processing in this study are illustrated in Figure 2. The equipment and materials consisted of strip plates, welding machines, chipping hammers, steel brushes, clamping pliers, complete self-protection tools, welding hoods, wearable device sensors, and smartphones.

First, the MetaMotion wearable device was attached to the wrist-hand of a welder that was considered to be the most influential part affecting the welding quality. Then the MetaMotion sensor was connected to the smartphone through a Bluetooth connection.

After the wearable sensors functioned properly and the material preparation was ready to use, the trainees started welding practices. Every finishing each layer, the weldments were cleaned with a wire brush. While the sensors recorded the data, the researcher recorded timestamps of the trainees' work activities such as preparation, welding, slag cleaning, and other activities. After finishing every layer, the recorded data was sent to the computer via a smartphone for data processing. Next, a signal graph was plotted from the recorded data of welding activity. The welding inspector (WI) and the researcher performed the inspection and plotting of correspondingly the resulting visual graphs. The data was then arranged in parallel to make it easier to do the analysis, identifying the relationship between the visual inspection results and the motion discontinuity related to timestamps. If one or more types of welding defects occur, the researcher recorded the types of defects along with the causes of the defects based on the WI comments. If a welding defect is not identified in the first trial, it was given the information as no defect is detected on the data retrieval form. Similar processes were applied to all basic welding training sessions refer to the syllabus.
Figure 2. Experiment's equipment and Data Flow Processing

The output data of the wearable sensors was in the form of CSV (comma separated values), as shown in Table 4.

Table 4. Example of the initial data recorded and activity identification

| timestamp (+0700) | elapsed (s) | accx (g) | accy (g) | accz (g) | gyrox (deg/sec) | gyroy (deg/sec) | gyroz (deg/sec) | magx (µT) | magy (µT) | magz (µT) | Skill Lvl | ID |
|------------------|------------|----------|----------|----------|----------------|-----------------|-----------------|-----------|-----------|-----------|-----------|----|
| 2021-03-18T11.49.28.930 | 0          | 0.414    | -1.013   | -0.237   | -92.805        | 59.39           | -82.866         | 1.5E-05   | 7.8E-06   | 5.6E-05   | 1         |    |
| 2021-03-18T11.49.28.970 | 0.04       | 0.563    | -0.98    | -0.183   | -88.659        | 56.159          | -83.049         | 9.2E-06   | 4.8E-06   | 5.7E-05   | 1         |    |
| 2021-03-18T11.49.29.010 | 0.08       | 0.573    | -0.972   | -0.278   | -69.573        | 30.976          | -83.049         | 8.1E-06   | 3E-06     | 5.8E-05   | 1         |    |
| 2021-03-18T11.49.29.050 | 0.12       | 0.541    | -0.918   | -0.259   | -55.549        | 10              | -77.439         | 5.1E-06   | 0         | 5.8E-05   | 1         |    |
| 2021-03-18T11.49.29.090 | 0.16       | 0.708    | -0.892   | -0.278   | -51.22         | 13.415          | -67.5           | 5.5E-06   | 1.1E-06   | 5.8E-05   | 1         |    |
| 2021-03-18T11.49.29.130 | 0.2        | 0.685    | -0.86    | -0.249   | -42.683        | -1.89           | -56.28          | 5.9E-06   | 1.1E-06   | 5.9E-05   | 1         |    |
| 2021-03-18T11.49.29.170 | 0.24       | 0.663    | -0.775   | -0.208   | -35.488        | -10.915         | -47.683         | 5.1E-06   | -1.8E-06  | 6E-05     | 1         |    |
| 2021-03-18T11.49.29.210 | 0.28       | 0.594    | -0.668   | -0.228   | -26.159        | 10.61           | -43.171         | 5.5E-06   | -1.4E-06  | 5.9E-05   | 1         |    |
| 2021-03-18T11.49.29.250 | 0.32       | 0.646    | -0.53    | -0.289   | -16.585        | 34.268          | -50.244         | 7.8E-06   | -1.1E-07  | 5.9E-05   | 1         |    |
| 2021-03-18T11.49.29.300 | 0.36       | 0.704    | -0.406   | -0.201   | -3.659         | 43.476          | -64.939         | 6.3E-06   | -1.4E-06  | 5.9E-05   | 1         |    |
| 2021-03-18T11.49.29.330 | 0.4        | 0.823    | -0.373   | -0.185   | 10.732         | 26.402          | -87.317         | 5.1E-06   | -1.8E-06  | 6E-05     | 1         |    |
| 2021-03-18T11.49.29.370 | 0.44       | 0.832    | -0.368   | -0.22    | 24.207         | 14.634          | -112.256        | 5.1E-06   | -1.4E-06  | 6E-05     | 1         |    |
| 2021-03-18T11.49.29.410 | 0.48       | 0.877    | -0.33    | -0.111   | 24.512         | 9.573           | -131.951        | 4.4E-06   | 7.5E-07   | 6E-05     | 1         |    |
| 2021-03-18T11.49.29.450 | 0.52       | 1.02     | -0.322   | -0.195   | 20.854         | 13.049          | -143.659        | 5.1E-06   | 2.6E-06   | 6.1E-05   | 1         |    |

Table 4 is an example of the initial data recorded from the sensors: accelerometer, gyroscope, and magnetometer. The magnetometer values were always close to zero. Data preparation is arranged in the order of accelerometer, gyroscope, magnetometer, and labeled with activity identity, session identity, and subject identity.

An example analysis of the visual inspection results of weldment discontinuity and the related signal graph of motion discontinuities are illustrated in Figure 3. The results of the experiment from one of the sample trainees are depicted in Figure 3. As seen in the visual image, two welding defects appear: incomplete penetration and undercut. Incomplete penetration was caused by a too high travel speed preventing good penetration to the base metal. Undercut defects occurred because the electrodes...
passed too quickly through the welding edges preventing good fusion between filler metal dan base metal.

| No | Discontinuity Type     | Possible Cause                                                                 |
|----|------------------------|-------------------------------------------------------------------------------|
| 1  | Incomplete Penetration | Electrode not filled perfectly, so there is no good penetration because the travel speed is too fast |
| 2  | Undercut               | The base metal has been eaten but has not been filled, the waving is not long on edge, and the travel speed is too fast |

Figure 3. Example of weldment and motion discontinuities during welding practice

When a welding defect occurred, the graph changed its shape to become irregular with several fluctuation in contrast to those done by the instructor, appearing stable and smooth at the end of the welding. We identified a direct relationship between the results of the signal graph plot and the condition of the visual appearance of the weldment. The discontinuity number was then calculated to determine the skill grade of trainees. The result was the number of defects that occurred in the first training session, and then calculations were carried out for each welding. An example of welding discontinuity calculation for straight 1st welding session is shown in Table 5.

Table 5. Calculation of welding discontinuity for straight 1st welding session

| Sample id | Number of line | Layer | Discontinuity (sec) | Total disc in a line | Total Disc | Total elapsed (in sec) | Percentage disc (%) |
|-----------|----------------|-------|---------------------|----------------------|------------|------------------------|----------------------|
| Trainer   | 3              | 1     | IF 2               | 3 3                  | 3           | 283.96                 | 1.05                 |
|           | 2              | 3     | IP                 | 0                    | 0           |                        |                      |
| Trainee 1 | 3              | 1     | IF 2               | 3 3                  | 3           | 167.96                 | 17.86                |
|           | 2              | 15    | IP                 | 0                    | 0           |                        |                      |
| Trainee 2 | 3              | 1     | IF 2               | 3 3                  | 3           | 205.96                 | 8.25                 |
|           | 2              | 3     | IP                 | 0                    | 0           |                        |                      |
| Trainee 3 | 3              | 1     | IF 2               | 3 3                  | 3           | 134.96                 | 12.59                |
|           | 2              | 3     | IP                 | 0                    | 0           |                        |                      |
| Trainee 4 | 3              | 1     | IF 2               | 3 3                  | 3           | 301.92                 | 5.63                 |
|           | 2              | 5     | IP                 | 0                    | 0           |                        |                      |
| Trainee 5 | 3              | 1     | IF 2               | 3 3                  | 3           | 165.96                 | 11.44                |
|           | 2              | 2     | IP                 | 0                    | 0           |                        |                      |
|           | 3              | 8     | IP                 | 0                    | 0           |                        |                      |
The discontinuity number from sampling was also calculated for the straight 2nd welding session practices as shown in Table 6. The results showing that the number of discontinuities of the 2nd welding session are relatively decreased.

Table 6. Calculation of welding discontinuity for straight 2nd welding session

| Sample id | Number of line | Layer | Discontinuity (sec) | Total disc in a line | Total Disc | Total elapsed (in sec) | Percentage disc (%) |
|-----------|----------------|-------|---------------------|---------------------|------------|------------------------|---------------------|
| Trainer   | 3              | 1     | IF                  | 3                   | 3          | 283.96                 | 1.05                |
|           |                | 2     | IP                  |                     |            |                        |                     |
|           |                | 3     | Undercut            |                     |            |                        |                     |
| Trainee 1 | 3              | 1     | IF                  | 3                   | 3          | 283.96                 | 1.05                |
|           |                | 2     | IP                  | 2                   | 2          | 17                     | 15.33               |
|           |                | 3     | Undercut            |                     |            |                        |                     |
| Trainee 2 | 3              | 1     | IF                  | 2                   | 4          | 23                     | 149.96              |
|           |                | 2     | IP                  | 2                   | 2          | 9                      | 4.41                |
|           |                | 3     | Undercut            |                     |            |                        |                     |
| Trainee 3 | 3              | 1     | IF                  | 3                   | 11         | 234.48                 | 4.69                |
|           |                | 2     | IP                  | 2                   | 2          | 11                     |                     |
|           |                | 3     | Undercut            |                     |            |                        |                     |
| Trainee 4 | 3              | 1     | IF                  | 2                   | 2          | 6                      | 242.96              |
|           |                | 2     | IP                  | 2                   | 2          | 6                      | 2.47                |
|           |                | 3     | Undercut            |                     |            |                        |                     |
| Trainee 5 | 3              | 1     | IF                  | 4                   | 16         | 313.96                 | 5.09                |
|           |                | 2     | IP                  | 3                   | 6          |                         |                     |
|           |                | 3     | Undercut            | 6                   | 6          |                         |                     |

The overall data was given an identity according to the number of discontinuities for further processing by performing the feature extraction and analyzed using the SVM supervised learning algorithm. From these results, we can evaluate each trainee's progress by reference to the welding instructor's signal graph and its visual inspection result.

4. Results and Discussion
4.1. Analysis of Skill Trainees' Progress
The analysis of skill trainees was carried out by comparing the welding results of trainees and those of instructors for several sessions of welding practices. This analysis was executed in groups of trainees consisting of 5 trainees.

An example of the results between the trainees (left side) and those of the trainer (right side) from the 1st welding session can be seen in Figure 4. The welding results are still not satisfactory where the travel speed is still too fast, and the visual results of the weldments width are narrower. The first layer of welding is completed in 78.1 seconds. It can also be observed in the yellow box above that there is an indication of graphic irregularities or so-called motion discontinuity. The irregular graph is caused by the trainee's less stable hand movements, especially in maintaining the torch's height or electrode, so the welding acceleration is also unstable. It also is shown there is a change in direction at the end of the welding so that it seems to turn slightly from the previous welding path.

The trainer/instructor welding graph (right side) appears smooth and constant, indicating stable and consistent hand movements. It is different from the welding graph of the trainee in sampling 2; there is an irregularity in the shape of the graph. This indicates the unsteadiness of the trainee's hand movements when the welding proceeded. This irregular signal contrasted with the visual appearance of the instructor's welding results (right side), which were very smooth and perfectly filled, showing the stability of hand movements, and no welding defects appear at all.
| Type Of Welding | Trainee | Trainer |
|-----------------|---------|---------|
| Straight        | ![Image](image1) | ![Image](image2) |
| Weaving         | ![Image](image3) | ![Image](image4) |
| 1F              | ![Image](image5) | ![Image](image6) |

**Figure 4.** Examples of visual inspection and motion analysis straight welding 1st session

| Type Of Welding | Trainee | Trainer |
|-----------------|---------|---------|
| Straight        | ![Image](image7) | ![Image](image8) |
| Weaving         | ![Image](image9) | ![Image](image10) |
| 1F              | ![Image](image11) | ![Image](image12) |

**Figure 5.** Example of visual inspection and motion analysis straight welding 2nd session
The results of the straight welding session of sampling two at the 2nd session are shown in Figure 5. The difference observed in terms of travel speed can be seen, starting to approach the trainer/instructor's travel speed (session 1). In the second session, sampling one complete one-layer welding for 97.2 seconds. This indicates that the trainer's travel speed is closer to 118.4 seconds than achieved by the instructor. Furthermore, the stability of the hand movements of sampling two was shown in this 2nd welding session. However, it can be seen in Figure 5 that the welding results of trainees are not straight as seen in their visual appearance, indicating the trainees only focused on keeping the electrodes constantly flames and forgot to maintain the straightness.

In this analysis, it could be concluded that the trainees in session 2 is more progressive. It is shown in the graph of the two samplings, where there were no significant differences in graph irregularities, indicating the two samples performed welding stable and consistently. However, only a slight difference can be seen that the instructor (right) still looks better and straighter when compared to the welding results of the trainees (left). The trainer must take a little more wrist-hand movement practices to resemble the skill grade of the welding instructor.

After knowing the progress of the skill training of trainees by analysing their graph visually, then an analysis of the skills acquisition progress was executed using one of the machine learning methods, namely the Support Vector Machine (SVM).

4.2. Analysis of Trainees’ Skill Grade
This section explained how to do monitoring for training trainees using data processing in Matlab software[19]. Based on the data taken from the wearable sensors, the data was processed into MATLAB. An example of the feature extraction value is shown in Table 7.

Table 6 describes the feature and function extraction applied in this study and an example of the resulting extraction for two windows on the x-axis accelerometer. The significant difference in the extraction values between the trainees and the instructors can be seen in terms of the mean, root-mean-square, autocorrelation, spectral peaks, and spectral power values. It is this extraction value that typically distinguished welding signals between trainees and instructors, each of them has its own characteristics.

Table 7. Example of the results of the accelerometer feature extraction x trainees and instructors

| Features                  | Function                                                                 | Trainer / instructor | Trainee |
|---------------------------|--------------------------------------------------------------------------|----------------------|---------|
| Mean                      | \( \bar{w} = \frac{1}{N} \sum_{i=1}^{N} w_i \)                          | 0.3630               | 0.1172  |
| Root Mean Square (RMS)    | \( \mathrm{RMS}(w) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} w_i^2} \)          | 0.0935               | 0.0905  |
| Auto-correlation          | \( d_{\text{ACF}}(x,y) = \sqrt{\sum_{l=1}^{L} (\phi_{il} - \phi_{yl})^2} \) | 2.1891               | 2.0491  |
| Spectral Peaks            | \( h(k_p) = \frac{|X(k_p)|}{\sqrt{|X(k_p) - |X(k_y)| + |X(k_y) + |X(k_y)|}/2}} \) | 0.3417               | 0.4272  |
| Spectral Power            | \( S_m[n] = \frac{2KP}{\sum_{l=0}^{L} \sum_{n=0}^{N} |\hat{a}_{ml}[n]|^2} \) | 0.0282               | 0.0865  |

The graphic signals is distinguished by the feature extraction value, as shown in Table 7. The extracted data were then classified simultaneously using the Support Vector Machine method. The extracted feature data were plotted as points in n-dimensional space (where "n" is the feature's quantity
of features). The value of each feature was a specific coordinate value. These values were used to differentiate welding trainees’ grades as well as instructors. This process was carried out for all extraction features and is also applied to the accx, accy, aczz, gyrx, gyry, gyrz, magx, magy and magz axes simultaneously.

After the feature extraction value appears, training data are carried out for each type of welding session. An experiment was conducted by taking a sample of training data for straight welding, monitoring for training progress. This process starts with importing data and selecting the classification method using the MatLab software, as shown in Figure 6.

![Figure 6](image)

**Figure 6.** The process of importing data and selecting the classification method

In Figure 6, it can be seen the steps of importing data and selecting the classification method, specifically the quadratic SVM method. The next step is the data training process for classifying trainee skill grades. One reason to select the SVM classifying method from the other machine learning methods was the ability to show the vector distances of classification results as shown in example of the scatter in Figure 8.

![Figure 8](image)

**Figure 8.** Example of the straight welding (a) 1st session and (b) 2nd session (mean accelerometer-...
Figure 7(a) showed an example of a scatterplot of the mean value for the x-axis accelerometer. Observing the scatterplot image indicated that the instructor's skills grade still could not be achieved by all trainees, where the red and yellow points still separated with a distance separating from the blue points. In this case, trainees had to perform more practice of wrist-hand movements to increase the skill grade.

The scatterplot of the 2nd straight welding session is shown in Figure 7(b). Each trainee achieved higher skills grades than those previously done in the first session, represented by the closer distance at the graphic plots (shown in the circles and arrows). A similar scatter plot can be applied to all available sensors, nine-axis degrees of freedom with five feature extractions.

The method of SVM works was by finding the hyperplane with the most significant margin. The hyperplane was the dividing plane between the data classes, while the margin was the distance between the hyperplane and the closest data in each category. The SVM worked by looking at several different characters in one and grouping them based on the feature extraction applied.

In this case, the welding skills of the instructors and trainees had different feature extraction values. These differences were then grouped and made as to type 1 of class (skill grade). The analysis using a scatterplot for every feature extraction could be used to monitor and assess the progress of skills acquisition for each trainee.

![Figure 7(a) and 7(b)](image)

**Figure 7.** Scatterplot of the mean value for the x-axis accelerometer.

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**Figure 8.** Confusion matrix test data in (a) 1st session and (b) 2nd session

Figure 8(a) shows the resulting confusion matrix for the training data consisting of 120 data windows. The 120 data windows consisted of 31 trainer data windows (grade 1) and 89 trainee data windows divided into four classes (grades 3, 4, 5, and 7). The results showed the following:

1. The SVM method can predict with an accuracy of 100% correct for trainer/instructor data (class 1 in true class)
2. The SVM method can correctly predict grades 3, 4, 5, and 7 with accuracy of 84.8% 86.4%; 81.3%; and 72.2% respectively.

It is meant that no trainee achieves similarity with those of the trainer's movement pattern. Then, each trainee had to perform welding movement training individually. After trainees did the practices, each trainee was performed for the data testing at the 2nd session to assess the progress of their skill acquisition.

Figure 8(b) displays the resulting confusion matrix for the test data of the second session consisting of 95 data windows. The 95 data consist of 27 windows for grade 3, 23 windows for grade 4, 27 windows for grade 5, and 18 windows for grade 7. The results present the following:

1. Subject with grade 3 in the 1st session shows significant progress to approach trainer motion, 20 of 27 windows predicted as 1st grade.
2. Subject with grade 4 in the 1st session shows stagnancy progress to approach trainer motion, 10 of 23 windows predicted as 4th grade.
Subject with grade 5 in the 1st session shows stagnancy progress to approach trainer motion, 17 of 27 windows predicted as 5th grade.

Subject with grade 7 in the 1st session shows instability progress to approach skill trainer motion, showing the predicted skills evenly distributed in many grades.

It has been shown above that closer similarity of the trainee's motion pattern to those of the instructor means the skill acquisition process is considered progressive. This fact was confirmed by the decreasing number of defects in the 2nd session. The outlined procedure of skill level assessment has also provided a more systematic and transparent explanation. The trainees could focus on practices of minimizing improperly wrist-hand motions to increase their skills grade closed to the instructor. It is important to note that methodological problems in the study may limit our interpretations. Because of the covid-19 pandemic, the number of trainees was limited, and the available time for welding practices until the trainee's skill level achieved the instructor level was not available.

Further study is also required to explore the possibility of using a similar approach on the professional welder training course. The other skills grade classifications based on the artificial intelligence techniques such as the Multi-Layer Perceptron (MLP) and the Deep Learning (DL) are also worth to be explored.

5. Conclusion

We conducted the study of monitoring and assessment of trainee's skill grades using wearable sensors in the basic welding training course. The skills grade of trainees has been analyzed based on the signal graph of the motion discontinuity and corresponding welding defects, showing a clear relationship. A validation was then carried out with the results of data processing analysis using the SVM machine learning method available in Matlab software by Mathworks. It was concluded that this monitoring and assessment method using the proposed wearable sensors could provide a clearer and more systematic way to achieve the certain welding skills grade of the trainees. The Other significant contribution of this study has inspired a possibility to develop a system for remote assessment of welder's skill level based on the graphical analysis of the welder's wrist-hand motion.

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