Acoustic based classification of transfer modes in gas metal arc welding

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ABSTRACT

Gas Metal Arc Welding (GMAW) is a welding process which involves forming an electric arc between a consumable wire electrode and a metal work piece while protecting the arc from contaminants using a shielding gas. In this form of welding, there are several varying ways in which the molten droplets can be transferred from the end of the welding wire into the weld pool known as transfer modes. Identifying these transfer modes is crucial in monitoring and controlling the welding process, especially in automated applications such as industry 4.0 manufacturing lines. Currently in industry, these transfer modes can be identified by expert welders by using the sound signal that is generated throughout the welding process. However, there has been limited research on using the acoustic signal to detect these transfer modes in automated welding applications.This paper explores a new method of automatic GMAW transfer mode detection using machine learning techniques to analyse the acoustic signal generated during the welding process. Several time and frequency domain features are extracted from the acoustic signal and used to train a support vector machine classifier to accurately classify the transfer modes. In addition to this, a new feature selection algorithm is proposed to improve the prediction accuracy of the support vector machine classifier and a final prediction rate of 94% was achieved. This high prediction rate demonstrates the feasibility and promising accuracy of using the acoustic signal as a basis for transfer mode classification in future smart welding technology with real-time adaptive feedback control.

1 INTRODUCTION

Gas Metal Arc Welding (GMAW) more commonly known as MIG/MAG welding is an electric welding process in which a consumable metal electrode is used to melt two base materials together while being protected via a shielding gas. As the manufacturing industry leads further towards automation, the demand for automated welding systems is increasing (Adewole 2019). Due to its fast welding speed and ease of use, automated GMAW systems are becoming more and more popular. However, despite the advantages, GMAW can suffer from a variety of arc instability issues which can lead to several common welding defects occurring, such as porosity, lack of penetration and burn through (Kah, Latifi et al. 2014). These arc instability issues are caused by changes in what is known as a transfer mode.

Transfer modes in GMAW are the method in which the consumable welding electrode melts and transfers material into the molten weld pool. These transfer modes are influenced by a number of different factors including shielding gas composition, gas flow rate, current, voltage, wire feed speed, welding speed, electrode diameter, Contact tip to workpiece distance, and material composition. These transfer modes are classified into two main groups by (Scotti, Ponomarev et al. 2012), contact transfer, and free flight transfer modes. Traditionally these transfer modes are normally able to be detected by expert welders using a combination of audio and visual cues (Tam and Huissoon 2005). However, this ability is lost in automated welding applications.

Previously, researchers have investigated the feasibility of using the generated acoustic signal as a means of detecting the transfer modes in the GMAW process. One of the earliest investigations was carried out by (Carlson, Johnson et al. 1990) who investigated the acoustic, current and voltage signals obtained by short circuit, spray and streaming transfer modes. Similarly, (Saini and Floyd 1998) investigated the feasibility of using the acoustic signal to monitor the welding process in real time as a means of online quality control. (Pal, Bhattacharya et al. 2010) also investigated the acoustic emissions generated during pulsed transfer modes for online monitoring and fault detection. Recently (Zhao, Qiu et al. 2018) developed a transfer mode detection model using the acoustic signal and Gaussian Mixture Model.

This paper aims to further improve the accuracy of the transfer mode detection algorithm introduced in previous work (Cullen, Zhao et al. 2021). In this paper, the GMAW process is classified into 6 different transfer modes; Short Circuit, Globular, Spray, Interchangeable, Explosive, and a final group to indicate no droplet transfer. Bead on plate welds are performed to replicate these 6 different transfer modes while synchronised acoustic, current, voltage, gas flow rate and high speed video footage where recorded. Using the acoustic signal, a SVM classifier is trained using a combination of time and frequency domain features.

2 EXPERIMENTAL SET UP

Figure 1 shows the test rig that was used to perform and record the GMAW process. In the performed experiments, a UniMig Razorweld 350 MIG welder was used with the torch being mounted to the end of an ABB IRB 140 6 axis robot. The welds were performed by moving the torch in a linear path in reference to the fixed metal workpiece. 32 individual welds were performed on 10 mm mild steel plates using 0.9 mm ER70S-6 welding wire. Half of these tests were performed using pure argon gas with the other half using a mixed consisting of 93% argon, 5% carbon dioxide and 2% oxygen. Each test was performed under a different combination of parameters outlined in Table 1 with the intention of replicating a range of different transfer modes with each weld bead being approximately 200 mm long.

The acoustic signal was recorded using a GRAS 40 PH free field microphone and was mounted on the robot manipulator 300 mm from the welding torch. In addition to the acoustic signal, a high-speed camera along with current. voltage, gas flow sensors were also used to analyse the welding process. A Basler ace 640-750um USB camera recording at 2000 fps was used in combination with two 660 nm bandpass filters to record the droplet transfer process. A LEM HTA 300-S current sensor was installed around the welding torch cable to record the current and the welding voltage was measured directly from the positive welding torch cable to the negative workbench clamp. A miller arc agent gas flow sensor was installed along the welding torch gas line to measure the gas flow rate to the welding torch. All of these signals were captured using a National Instruments cDAQ 9185 chassis containing a NI 9215 Analogue Voltage Input module to capture the current, voltage and gas flow rate signals and a NI 9234 Sound and Vibration module to capture the acoustic signal. The captured signals were captured and stored using a custom program developed using National Instruments Labview.

In order to replicate potential real-world applications and to test the robustness of the system, the experiments were performed in a noisy factory environment.

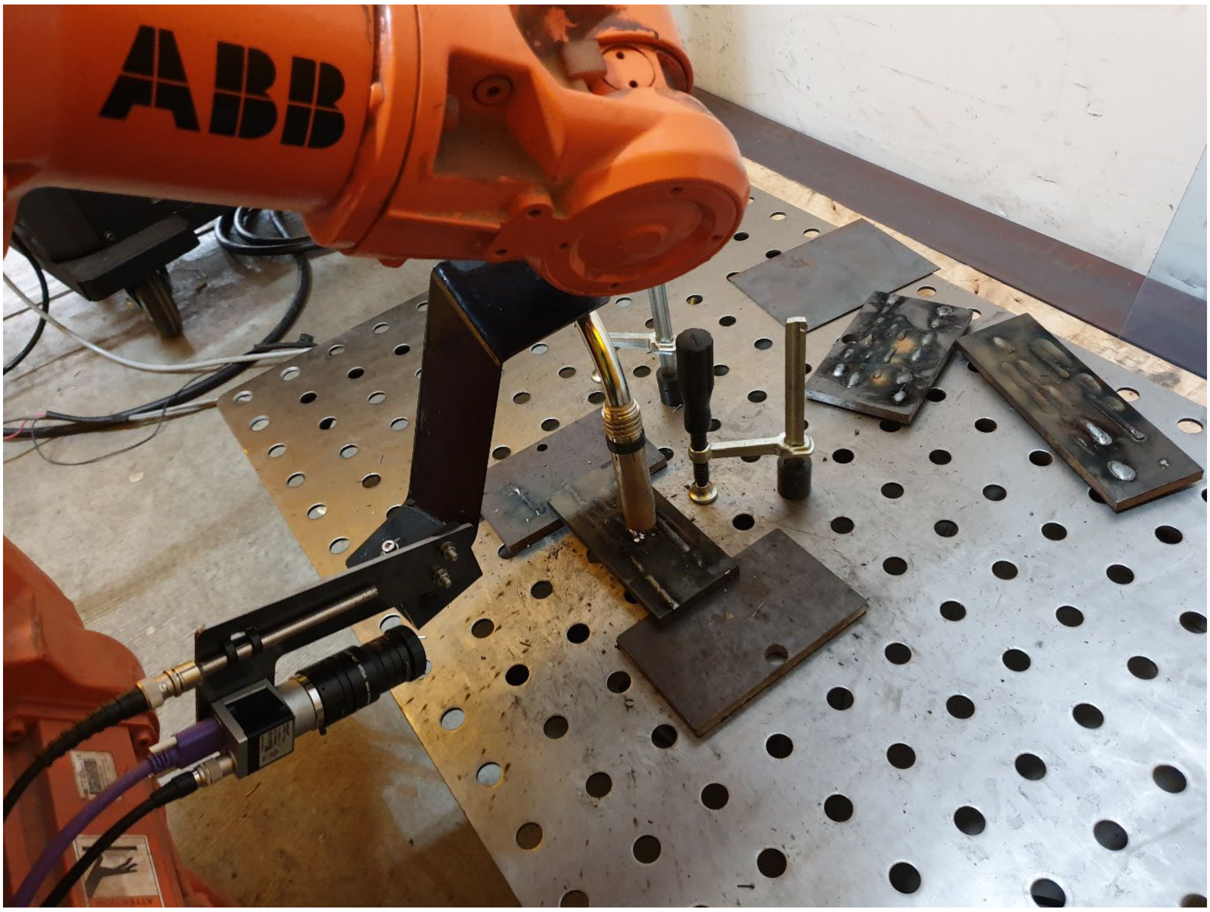

Figure 1: Test rig

Table 1: Experimental parameters

Test Number	Transfer Mode	Gas Composition	Voltage	Inductance	Gas Flow Rate	CTWD	Travel Speed	Wire Feed Rate	Gun Angle
1	SC	Argon	20	0	20	16	3.5	5	Push
2	SC	Argon	18	0	20	16	3.5	4.5	Push
3	SC	Argon	22	50	20	15	3.5	6	Pull
4	SC	Argon	20	30	20	15	3.5	7.5	Pull
5	SP	Argon	30	0	20	18	7	10.6	Push
6	SP	Argon	28	0	20	18	7	9.2	Push
7	SP	Argon	34	0	20	18	7	12.7	Pull
8	SP	Argon	30	0	20	18	7	10.6	Pull
9	E	Argon	20	0	0	16	3.5	5	Push
10	E	Argon	30	0	0	18	7	10.6	Push
11	SP	Argon	28	0	20	18	7	10	Pull
12	G	Argon	28	0	20	28	7	10	Pull
13	G	Argon	27	0	20	28	7	9.2	Pull
14	I	Argon	31.5	30	20	23	7	8	Push
15	I	Argon	27	0	20	16	7	8.5	Push
16	I	Argon	26	50	20	16	7	9.2	Push
17	SC	Mix	20	30	20	16	3.5	5	Push
18	SC	Mix	18	0	20	16	3.5	4.5	Push
19	SC	Mix	22	50	20	15	3.5	6.4	Pull
20	SC	Mix	20	30	20	15	3.5	7.5	Pull
21	SP	Mix	30	0	20	18	7	10.6	Push
22	SP	Mix	28	0	20	18	7	9.9	Push
23	SP	Mix	34	0	20	18	7	12.7	Pull
24	SP	Mix	30	0	20	18	7	10.6	Pull
25	G	Mix	30	0	20	20	5.5	6.4	Pull
26	G	Mix	30	50	20	19	5.5	7.1	Push
27	G	Mix	29	0	20	18	7	9.2	Push
28	G	Mix	29	0	20	18	5.5	6.4	Push
29	E	Mix	25	0	0	18	5.5	7.1	Push
30	I	Mix	30	0	20	18	7	8.5	Push
31	I	Mix	27	0	20	16	7	8.5	Push
32	I	Mix	26	50	20	16	7	9.2	Push

3 METHODOLOGY

3.1 Signal Breakdown

Once the 32 signals using the settings outlined in Table 1 had been collected, the high-speed video footage was analysed alongside the acoustic, current, voltage and gas flow signals to analyse the transfer modes and droplet transfer process. After analysing these signals, it was found that the original transfer mode classification outlined in Table 1 did not accurately describe the transfer mode across the entire length of each recorded weld bead. Therefor it was decided each signal would be broken down into 20 ms segments, with each segment manually classified as one of the five targeted transfer modes based on the reviewed high-speed footage. This segment length was chosen as it is long effectively capture a complete short circuit or globular transfer, while not being too long such that temporary transfer mode changes are drowned out by the dominant transfer mode.

3.2 Feature Extraction and Selection

To extract the critical information from the raw sound signal a large selection of time and frequency domain features are extracted. However, to reduce the dimensionality of the feature set, a new feature selection algorithm was designed. This feature selection algorithm aims to select the optimal feature set which maximise the average interclass distance between the probability distributions of each transfer mode. This feature selection algorithm is detailed below in Figure 2 and in Equations (1)-(5).

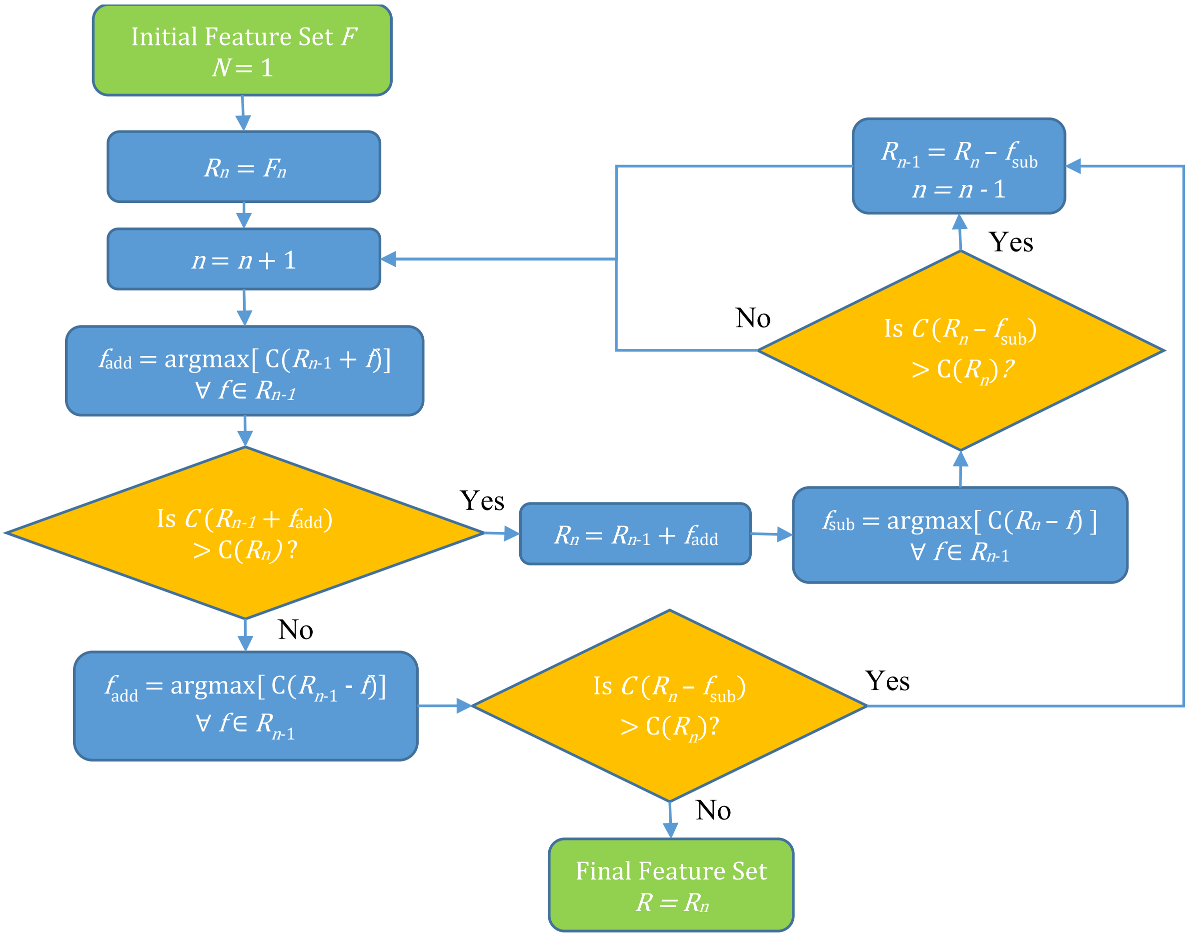

Figure 2: Feature selection algorithm

$$D_B = \frac{1}{8}(\mu_i - \mu_j)^T \Sigma^{-1}(\mu_i - \mu_j) + \frac{1}{2}\ln\left(\frac{det\Sigma}{\sqrt{det\Sigma_i + det\Sigma_j}}\right) \tag{1}$$

$$\Sigma = \frac{\Sigma_i + \Sigma_j}{2} \tag{2}$$

where D_B is the Bhattacharyya distance, μ_i and μ_j are the means, and Σ_i and Σ_j are covariance matrices for the *i*-th and *j*-th multivariate probability distributions.

$$D_{min} = \min\left(D_B(i,j)\ |i \in \{1, \dots, M\}, j \in \{i+1, \dots, M\}\right) \tag{3}$$

$$D_{avg} = \frac{2!\,(M-2)!}{M!}\sum_{i=1}^{M}\sum_{j=i+1}^{M} D_B(i,j) \tag{4}$$

$$C = \frac{(D_{min} + D_{avg})}{L} * \sqrt{1 + c_0^2} \tag{5}$$

where *M* is the number of classes, *C* is the normalising threshold, and *L* is the number of features currently selected.

3.3 SVM Training

To detect and classify the correct transfer modes from the recorded dataset, a multiclass SVM model is used. The SVM classifier is trained using the feature set previously selected by the feature selection algorithm. These selected features for each of the 20ms segments are then used to train the SVM classifier. The SVM Classifier is trained and tested using 10-fold cross validation to maximise the accuracy of the final result. (49615 segments used)

4 RESULTS

The SVM classifier was able to accurately predict the transfer mode of each 20ms segment with and accuracy of 94.1%. Figure 3 below shows the confusion matrix detailing these results.

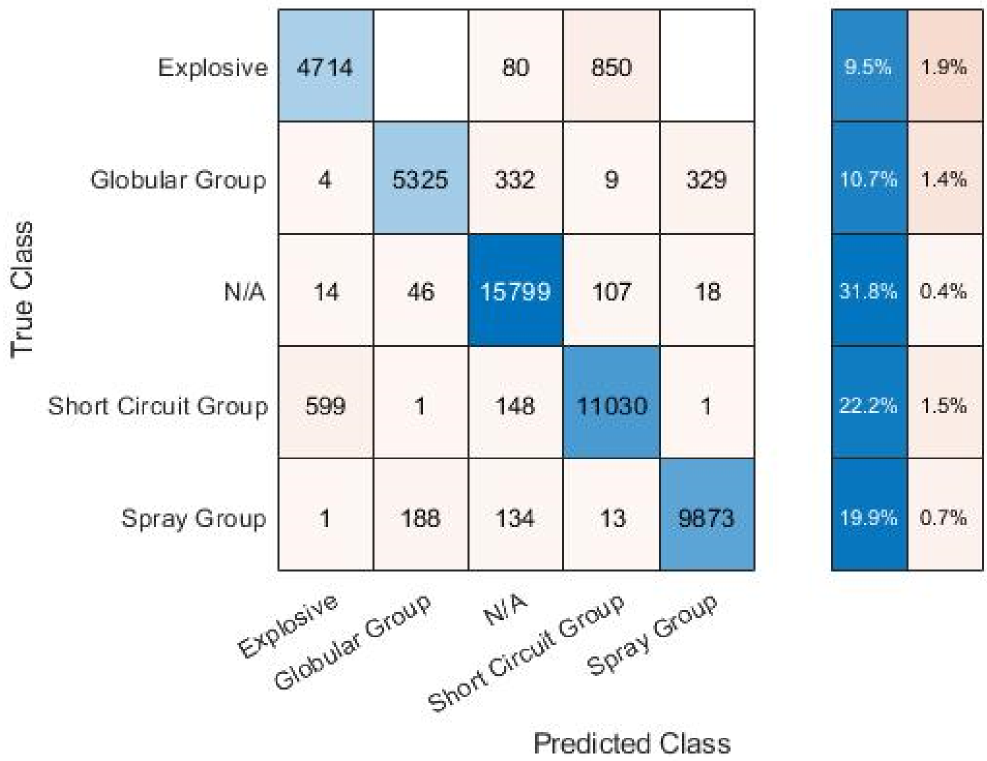

Figure 3: SVM confusion matrix

When further analysing the results found in Figure 3, it can be seen that there are a few key areas in which the model tends to have a higher misclassification rate. In particular, the model has a high misclassification rate between globular and spray transfer modes as well as short circuit and explosive transfer modes. To understand why these areas contained the largest percentages of misclassification, each of the misclassified segments were re-examined.

When looking at the misclassification results of the globular and spray transfer groups, it was found that majority of the misclassifications existed in a grey area between the 2 different transfer modes. This is illustrated in Figure 4 which shows a standard spray transfer, a standard globular transfer, and one of the misclassified segments in between. From the current literature definition of spray and globular transfer (Scotti, Ponomarev et al. 2014), a droplet is considered to be in spray transfer when the diameter of the droplet is less than or equal to the diameter of the welding electrode. When the diameter is larger it is considered to be in globular transfer. Using this classification system, it can be seen that the misclassified segment is technically a globular transfer, however it is right on the border of being a spray transfer. Similar to the misclassification between globular and spray transfer, a similar phenomenon can be observed with short circuit and explosive transfer modes.

Figure 5 shows both a standard short circuit and explosive transfer mode. In both modes, the electrode makes contact with the weld pool creating a short circuit before transferring material into the weld pool. However, due to the lack of shielding gas, the explosive transfer process is not as smooth as in short circuit transfer, leading to a more violent explosion and turbulent weld pool. When analysing the misclassified segments between these two modes, it can be seen that majority of the misclassified segments occur when there is either a particularly turbulent transfer of material in a short circuit transfer, or more commonly, a particularly smooth transfer of material in an explosive transfer. Technically, despite the lack of gas, if the material smoothly transfers from the end of the electrode to the weld pool while short circuiting, it should be classified as a short circuit transfer mode. Because of this, many of the misclassifications between explosive and short circuit transfer are technically correct and should not be counted as misclassifications. Taking both of the above cases into account, it can be concluded that the overall accuracy of the SVM classifier's may actually exceed 94% due to the ambiguity of some of the manual classifications.

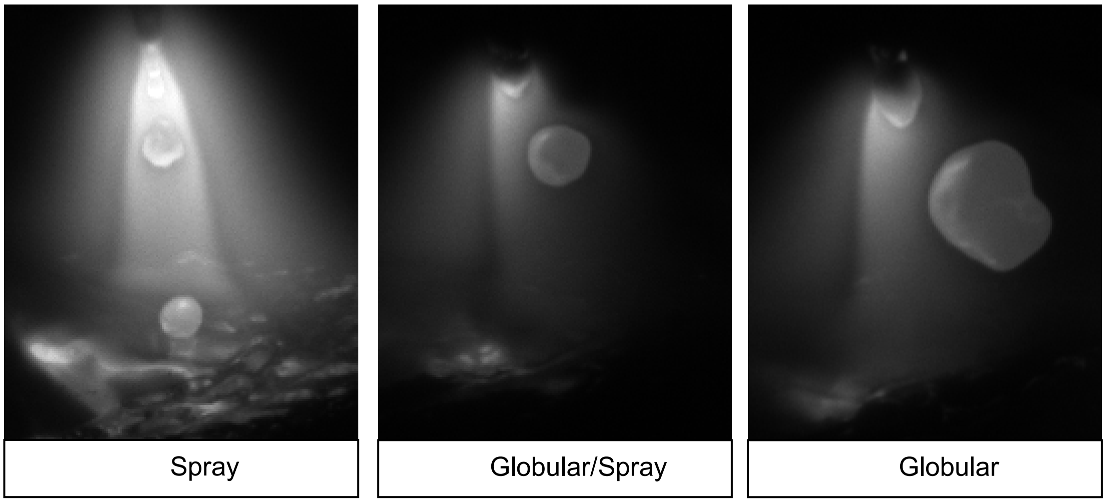

Figure 4: Globular/spray compairson

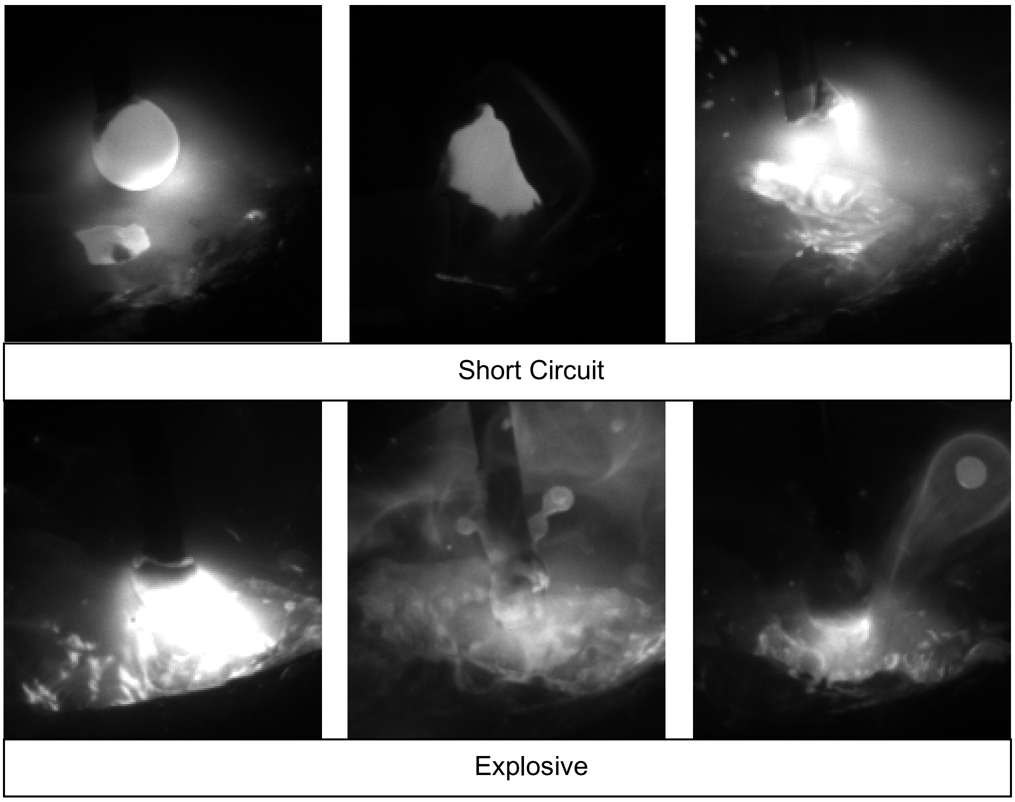

Figure 5: Short circuit/explosive comparison

5 CONCLUSION

In this paper, a new GMAW transfer mode detection system based on the acoustic signal. This transfer mode detection system was able to accurately detect the natural transfer modes that occur in GMAW with a prediction accuracy of 94%. The high prediction accuracy and ease of use as a plug and play solution shows promise in adapting the model to be used in real time to effectively monitor automated welding processes. Future work involves adapting the transfer mode detection system to detect instabilities in the welding arc, allowing for defects to be detected in real time.

6 ACKNOWLEDGEMENTS

The authors would like to thank Scott Automation & Robotics for their permissions to use their equipment and factory space to perform the tests undertaken in this paper.

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