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Multi-Level Welding Quality Fault Discovery of an Intelligent Production Line by Using Taguchi Quality Loss Function and Signal-Noise Ratio

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ABSTRACT The rapid and extensive pervasion of intelligent manufacturing concept has enhanced the revolution of the industry. A great interest has arisen in the past five years for the quantity and quality of an intelligent production line. Despite this fact, research areas, such as performance evaluation and fault discovery of these intelligent production lines based on different sets of criteria and techniques, are conspicuously untapped. This paper aims to contribute to the fault discovery by proposing an integrated approach combining the Taguchi quality loss function (QLF), the signal–noise ratio (SNR), and the relief method. First, in order to measure the theoretical value of quality deviation, the Taguchi QLF is introduced. By using the QLF, the information set is transformed into the quality features set. Thereby, the multiple quality features can be fused by using the SNR. Moreover, the features need to be reduced by the relief algorithm, if necessary. The Taguchi QLF-SNR allows decision makers to set tolerance thresholds for multi-levels (characteristic-level/unit-level/system-level) to discover the welding quality fault in the process of production line. Also a case study is presented to verify the feasibility and accuracy of the approach.

INDEX TERMS Taguchi quality loss function (QLF), signal-noise ratio (SNR), relief, feature selection, fault discovery, welding quality.

I. INTRODUCTION

Lots of surveys show that, the solar cells welding industry with sophisticated operation and control has always been one of the leading enterprises because of the advancement in automation and information [1], [2]. With the widely used intelligent production line of solar cells series welding machine system, the approaches to the quality fault discovery become the urgent needs for this Industry [3]. By analyzing the process data, the evidence-driven decision of quality fault discovery can be made.

The traditional methods for fault discovery are shown in FIGURE 1.There are three types in total: Methods based on analytical model (Parametric Estimation, State Estimation, Parity Space, and some other analysis-based approaches), Methods based on knowledge (Expert System, Fuzzy Illation, Machine Learning, and some other knowledge-based approaches), and Methods based on signal processing (Wavelet Analysis, Spectra Analysis, and some other observer-based approaches) [4].

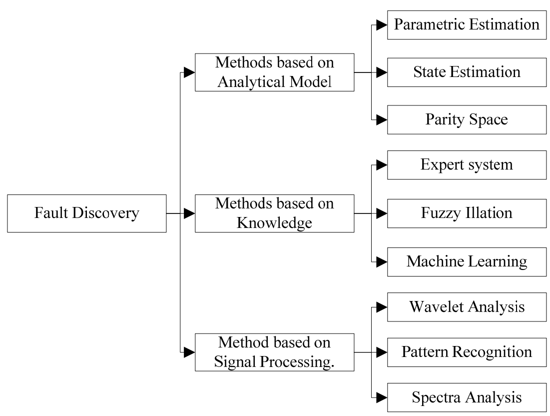

FIGURE 1. Methods for fault discovery.

Khan and Sharma [5] proposed hybrid expert system utilizes dissolved gas in oil analysis techniques to diagnose for fault condition of power transformers, where contains

TABLE 1. The comparison of the main fault discovery methods.

	Analysis	Knowledge[5, 6]	Observer[7, 8]
Quick Detection	?	√	√
Isolability	×	√	√
Robustness	√	√	√
Adaptability	√	×	×
Explanation Facility	√	√	×
Modeling Requirement	√	√	?
Multiple fault Identifiability	√	×	√

the Roger's Four Ratio Method, the Northern Technology & Testing (NTT) Flag point method, generation rate ratio method and Total dissolve combustible Gas method. Mani and Jerome [6] presented Intuitionistic Fuzzy expert System (IFS) to diagnose several faults and the proposes method was applied to an independent data of different power transformers and various case studies of historic trends of transformer units. It had been proved to be a very advantageous tool for transformer diagnosis and upkeep planning. Keswani *et al.* [7] developed a fault diagnostic system in a multi-level inverter using wavelet modulus maxima The wavelet modulus maxima of output phase voltages were used to detect faulty phase (leg), and wavelet modulus maxima of DC bus currents were used to detect fault type and fault switch.

Although the knowledge an observer based approaches are wildly used, the weakness in the adaptability [8] cannot be ignore. What is more, the knowledge-based approaches cannot deal with the multiple fault classification and the observer-based approaches cannot do well in explanation facility. The comparison of the three types is listed in TABLE 1 [4].

In this study, the analysis-based approach (Taguchi Quality Loss Function and Signal-Noise Ratio, QLF-SNR) has been chosen to measure the welding features. While there are many current highlight studies about the quality prediction by Taguchi approach for various fields. Dao and Huang [9] presented a multi-response optimal design for new two degrees of freedom compliant mechanism (TDCM) by the use of the Taguchi method, response surface methodology, grey relational analysis and entropy weighting measurement technique. Response surface methodology was utilized for modeling the relationship between design parameters and two responses with grey relational grade. And Dao *et al.* [10] developed a hybrid Taguchi-cuckoo search (HTCS) algorithm to optimize overall the quality responses, simultaneously. The length, width, and thickness of flexure hinges were considered as design variables. The Taguchi's L_{16} orthogonal array was used to establish the experimental layout and the S/N ratios of each response are computed. While this method does not have the ability of fault isolation, Machine Learning can be introduced in the future work to solve this problem. And the Machine Learning's calibration values can be gotten from this method.

The rest of the paper is organized as follow: in Section 1, the Materials and methods is described in details; the Section 2 presents the case study of the Characteristic-Level; the Section 3 takes the Unit-Level as an example to analyses the operation mechanism of the quality fault discovery; And in the last section, we conclude the paper and consider the future work.

II. MATERIALS AND METHODS

A. THE MEASUREMENT OF WELDING QUALITY FEATURE IN INTELLIGENT PRODUCTION LINE BY QLF

QLF is introduced by Genichi Taguchi as a tool for assessing the quality deviation degree incurred by varying product performance from the nominal [11], [12]. And it is used to represent the theoretical value of quality deviation [13]. QLF is a prominent quality engineering method has been applying to a variety of situations, including healthcare [14], real estate [15], [16], and supplier evaluation and selection models [17]–[19].Its popularity testifies to the merit of its quality philosophy.

From Dr. Taguchi's perspective, a product creates quality loss if it deviates from the target value [20], [21]. And the quality control approach is that products determine acceptable if their features' measurement falls within the specification limit [22]. In this study, the QLF is used to calculate the deviation of each quality feature. According to the mechanism of QLF, the function of QLF can be divided into three types [23]:

1)Target-is-best features: this would be the case, for example, when the quality feature is the precision of assembly ($20^{+0.3}_{-0.3}$) and the target value is 20; the quality property fluctuates around the 20,the closer the precision of assembly get to 20and the smaller the fluctuation is, the better it is.

2) Higher-is-better features: this would be the case, for example, when the quality feature is the life-cycle of parts; the larger the life-cycle and the smaller the fluctuation is, the better it is.

3) Smaller-is-better features: this would be the case, for example, when the quality feature is the surface roughness and the target value is zero; the smaller the surface roughness and the fluctuation is, the better it is.

The function equations can be described in TABLE 2 as below:

Where y_i is a measurable quality feature. k is average loss coefficient and determined by the cost of the feature y_i. In this study, because the SNR is introduced, the results are dimensionless, so the k is set to 1. The T_i is the target value of y_i And the T_U^i, T_l^i, is the upper value and lower value of specification limit or quality tolerance [24].

Generally, quality is a complex and multifaceted concept. Some researchers have surveyed several different aspects. Dr. Taguchi recommends the use of criteria SNR [13] to fuse the multiple quality features.

TABLE 2. The Quality loss function equations.

Type	Quality Loss Function
y_i Target-is-best features	$L_T(y_i)=k\left(\frac{y_i-T_i}{T_U^i-T_l^i}\right)^2$
y_i Higher-is-better features	$L_L(y_i)=k\left(\frac{y_i-T_U^i}{T_U^i-T_l^i}\right)^2$
y_i Smaller-is-better features	$L_L(y_i)=k\left(\frac{y_i-T_l^i}{T_U^i-T_l^i}\right)^2$

Definition 1: Set the product quality features fluctuate randomly. According the mathematical statistics, let μu be the mathematical expectation and σ^2 be the variance. As the following equations:

$$\eta=\frac{\mu^2}{\sigma^2} \tag{1}$$

Where η is SNR, which is regarded as the index of fluctuation to evaluate the quality features. The larger the η is, the more stable the product quality is and the smaller the quality loss is. Dr. Taguchi introduces the concept of SNR into QLF and the combination rules as shown in the following TABLE 3:

TABLE 3. The quality loss function equations.

Type	SNR equations
Target-is-best features	$\eta_T=10lg\frac{\mu^2}{\sigma^2}\approx 10lg\frac{\bar{y}^2}{s^2}$ where, $\bar{y}=\frac{1}{n}\sum_{i=1}^{n}y_i$, $s^2=\frac{1}{n-1}\sum_{i=1}^{n}(y-\bar{y})^2$
Higher-is-better features	$\eta_L=10lg(\mu^2+\sigma^2)\approx -10lg\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right)$
Smaller-is-better features	$\eta_S=10lg\left(\frac{1}{\mu^2+\sigma^2}\right)\approx -10lg\left(\frac{1}{n}\sum_{i=1}^{n}y_i^2\right)$

Based on this, the SNR value is used to represent the contribution of the features quality loss for the whole quality loss. The contribution can be used to weight the multiple quality features in the linear combination, and the expressions of the weights as follows:

$$\lambda_i=\frac{\frac{1}{\eta_i}}{\sum_{j=1}^{n}\frac{1}{\eta_j}} \tag{2}$$

So, the multivariate quality loss function is expressed as:

$$L(y_1,y_2,\ldots y_n)=\sum_{i=1}^{n}\lambda_i L(y_i) \tag{3}$$

Where:

λ_i—Loss weight of y_i.

$L(y_i)$ —Loss function of y_i.

TABLE 4. Methods of feature selection.

Strategy		Method
Embedding	Global search	Branch and Bound
	Random search	Combine with Intelligence algorithm
	Heuristic search	Sequential Forward Selection
		Generalized Sequential Forward Selection
		Sequential Backward Selection
		Generalized Sequential Backward Selection
Evaluation	Filter	Probability Metrics
		Euclidian Distance and Mahalanobis Distance
		Information Entropy Method
		Decision Tree Filtering Method
	Wrapper	Fisher Method

B. FEATURE SELECTION

The essence of feature selection is to find out the effective features to describe the performance. Nowadays the most wildly used method can be divided into the following three kinds: filter, wrapper and embedding [25], shown in TABLE 4.

Embedding strategy mainly contains global, random and heuristic search [26]:

1) The Branch and Bound Algorithm based on the global search strategy focus on the number of the subset elements in quality features. There are some problems: ① the number of subset element relies heavily on engineering experience; The determination of the number is different from person to person and could not be determined accurately. ② this method is based on the global search, whose computational complexity is very high, especially when the quantity of the data sample is large and with high dimensions.

2) The random search strategy needs to combine with intelligent algorithms, such as Simulated Annealing Algorithm (SAA), Taboo Search Algorithm (TS) and Genetic Algorithm (GA), etc. These methods can rank all the features and get better results. However, the method cannot determine the optimal or better subset by the global correlation ranking. What's more, the computational complexity increases exponentially.

3) The number of the methods based on heuristic search strategy is much more than others. Such as Sequential forward selection method (SFS), Generalized Sequential forward selection method (GSFS), Sequential backward selection method (SBS), and Generalized Sequential backward selection (GSBS).Among them, the correlation between SFS and GSFS algorithm is not considered, and the best subset is easy to show the loss of the feature with max individual contribution rate. While the SBS and GSBS algorithms based on calculation of the variable set, can get the criterion function accurately, but the computational complexity is the largest of all the above algorithms [27], [28].

Above all, this study intends to adopt the Relief method which is based on the inter-class and intra-class distance measurement to carry out the feature selection. And the Fisher method is used to verify the test.

The Relief algorithm is mainly used in binary classification which is suitable for the fault discovery in this paper, and the improved Relief-F algorithm can undertake multiple classifications. The essence of Relief Algorithm is to design a statistical vector, which represents the importance degree of each initial feature. The result of feature selection is the sum of subset weights. By setting the thresholds (τ) of the sum of subset weights, the Relief Algorithm determines the number (n) of features subset elements. Based on this idea, the problem of feature selection is transformed into to describe the importance degree of each feature [29]. The Relief algorithm is based on the method of inter-class and intra-class distance measurement, such as Euclidian Distance and Mahalanobis Distance. The sample is $D : (x_1, y_1), (x_2, y_2), \ldots, (x_m, y_m)$, $x_{i\,min\,1}$ stands for closest inter-class distance and $x_{i\,min\,2}$ stands for the closest intra-class distance.

Euclidian Distance can be described as following:

The distance inn-dimension Euclidian Distance $(x_1, y_1, z_1 \ldots)$, $(x_2, y_2, z_2 \ldots)$:

$$E_n = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2 + \ldots} \tag{4}$$

Mahalanobis Distance can be described as following:

The sample is $x = (x_1, x_2, \ldots x_N)^T$; the mean is $\mu = (\mu_1, \mu_2, \ldots \mu_N)^T$; the covariance matrix is $\sum$, and the Mahalanobis Distance is:

$$M(x) = \sqrt{(x-\mu)^T \sum^{-1} (x-\mu)} \tag{5}$$

The important degree of one feature j is

$$\xi^j = \sum_i -diff\left(x_i^j, x_{i\,min1}\right)^2 + diff\left(x_i^j, x_{i\,min2}\right)^2 \tag{6}$$

Where x_i^j stands the value of sample x_i on feature j, and the $diff\left(x_a^j, x_b^j\right)$ determined by the feature j and can be calculated as following:

1) The discrete features:

$$diff\left(x_a^j, x_b^j\right) = \begin{cases} 0, & x_a^j = x_b^j \\ 1, & others \end{cases} \tag{7}$$

2) The continuous features:

$$diff\left(x_a^j, x_b^j\right) = \left|x_a^j - x_b^j\right| \tag{8}$$

And what's more, the x_a^j, x_b^j has been normalized to the [0, 1].

C. THE PROPOSED ALGORITHM OF QLF-SNR FOR THE MULTI-LEVEL COORDINATION WELDING QUALITY FAULT DISCOVERY

This paper puts forward a multi-level quality fault discovery model in an intelligent production line based on QLF-SNR. Firstly, the welding process data can be divided into three levels (Characteristic-Level/Unit-Level/System-Level) to represent the welding features in different levels. In the following, calculate the deviation degree of the quality features by QLF-SNR; finally, decide the threshold to distinguish the abnormal and normal samples. Because there are much more features in the Unit-Level and System-Level, the Relief Arithmetic is utilized to select features. By using multi-stage synergy strategy, this method makes the fault discovery more targeted which can reduce the noise interference to some extent. This makes great significance on improving the accuracy of the discovery. The process is shown in FIGURE 2.

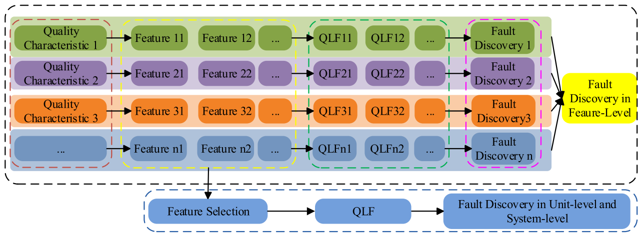

FIGURE 2. The process of mulit-level of Fault Discovery.

INPUT: Dataset.

OUTPUT: Multi-level welding quality fault discovery.

STEP 1: The data set is constructed from the information collected from sensors.

STEP 2: The feature set is generated by calculating the QLF of each feature set. The preprocessing includes normalization and dimensions reduction (only in Unit-Level and System-Level by using Relief Algorithm based on Mahalanobis Distance).

STEP 3: The abnormal threshold of QLF can be calculated by using SNR and the fault discovery are issued.

STEP 4: The accuracy of the method can be tested by comparing with Relief Algorithm based on Euclidian Distance and Fisher Method.

III. CASE STUDY OF CHARACTERISTIC-LEVEL

A. FEATURE CLASSIFICATION

The feature classification of processing quality of an intelligent production line is to select the industrial big data features which can influence the processing quality of the production line. Take the processing quality of an intelligent production line of solar cell as an example. All the features gathered from the production line are the System-Level-driven features. The line can be divided into 4 units (Inventory unit, Cutting unit, Welding unit, and Assembling unit) as the FIGURE 3 and the FIGURE 4 is the Welding Unit-Level.

The Welding Unit-Level mainly consists of 4 quality characteristic (fragmentation, incline, insufficient solder and spacing between cells). The characteristic can be classified into based-on-rules features and quantitative features.

Among them, the main quantitative factors of the fragmentation characteristic are the adsorption of negative pressure of

TABLE 5. Methods of feature selection.

Quality Characteristic	Classification	Features
Fragmentation Characteristic	The Features Based on Rules	1. The grab position of power cylinder and the placed position of battery cells on auxiliary feeding system; 2. The roughness of the mulit-platforms; 3. The grasp height between the robot and CCD platform; 4.The height of robot arm; 5. Some other features.
	Quantitative Features	1. The adsorption of negative pressure of supplementary feeding system 2. The pressure of wind knife 3. The adsorption of negative pressure of walking beam 4. The adsorption of negative pressure of CCD platform 5. The adsorption of negative pressure of the robot 6. The edge detection (left/right/up/down) 7. The angle detection 8. The rollover test of 180°
Incline Characteristic	The Features Based on Rules	1. The grab position of traction clamping jaw; 2. The roughness between the traction clamping jaw and cutting facet; 3. Some other features.
	Quantitative Features	1. Speed up time of traction servo deceleration 2. Speed down time of traction servo deceleration
Insufficient Solder Characteristic	The Features Based on Rules	1.Spray position of scaling powder; 2. The flatness of screen fabric; 3. The direction of tension force; 4. Some other features.
	Quantitative Features	1. The lamp power of Line A/B 2. The welding time of Line A/B 3. The temperature of welding platform
Spacing Characteristic	The Features Based on Rules	1. Whether there are fissure edge of conveyor belt and belt joint; 2. Whether the conveyor belt rollers are in the same beat; 3. Whether there are wanders when put down the cells; 4. Some other features.
	Quantitative Features	1. The adsorption of negative pressure of walking beam 2. The step distance

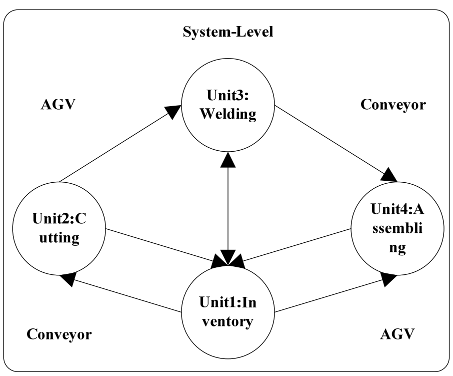

FIGURE 3. **The System-Level and Unit-Level of the solar cell production line.**

supplementary feeding system and walking beam, the pressure of wind knife and the edge detection, etc.

The main quantitative factors of incline characteristic include the time of speed up and down of the traction servo deceleration, etc.

The main quantitative factors of the insufficient solder characteristic include the lamp power and the welding time of Line A/B, the temperature of welding platform, etc. Just as the TABLE 5:

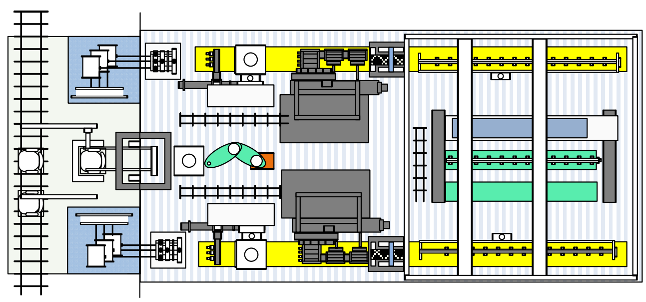

FIGURE 4. **The Welding Unit-Level of the solar cell production line.**

B. THE CHARACTERISTIC-LEVEL QUALITY LOSS MEASUREMENT AND FAULT DISCOVERY BASED ON QLF-SNR

In the 4 characteristics, eliminate the features based on rules. The quantitative features are shown as below in FIGURE 5:

Take the fragmentation characteristic as an example. The values' range of the based-on-rules features and quantitative features are as following in TABLE 6:

As shown in FIGURE 5 b), there are 11 features in the Fragmentation Characteristic.

And the TABLE 7 is the Taguchi method measurement of the 11 dimensions features:

TABLE 6. Standard values of features.

Features Based on Rules		Quantitative Features	
Features	Range	Features	Range
The grab position of power cylinder on auxiliary feeding line	0/1	the pressure of wind knife	0.18-0.25 Mpa
The placed position of battery cells on auxiliary feeding line	0/1	the adsorption of negative pressure of supplementary feeding system	-40 - -50 Kpa
The height of robot arm	Number	the adsorption of negative pressure of walking beam	-30 - -50 Kpa
Speed of Conveyor	Number	the adsorption of negative pressure of CCD platform	-18 - -20 Kpa
position of welding	0/1	the adsorption of negative pressure of the robot	-65 - -75 Kpa
Flip speed of upper/ lower adsorption mechanism	Number	the edge detection(left/right/up/down)	35-45 Pixels
Connecting position of Upper and lower adsorption mechanism	0/1	the angle detection	9-11 Pixels
Drop position of Upper and lower adsorption mechanism	0/1	the rollover test of 180°	0-20 Pixels
…	…	…	…

TABLE 7. The measurement of fragmentation characteristic.

	FC1	FC2	FC3	FC4	FC5	FC6	FC7	FC8	FC9	FC10	FC11
T_i	0.215	-45	-19	-70	-40	10	40	40	40	40	10
T_U^i	0.25	-34	-18	-65.1	-29	13	46	46	46	45	24
T_L^i	0.17	-51	-22	-76.2	-51	8	34	34	35	33	0
σ^2	0.000488	10.64378	0.632643	9.608537	39.20544	0.528488	9.492829	9.356568	10.33796	10.05889	42.71697
μ	0.205	-41.15	-18.8	-69.9	-39	10.5	41	40.5	42	44.5	20
η_i	19.35033	22.01644	27.47157	27.06297	15.88783	23.19343	22.48172	22.43793	22.32064	22.9417	9.714596
λ_i	0.0928	0.081562	0.065366	0.066353	0.113024	0.077423	0.079874	0.08003	0.08045	0.078273	0.184846

T_i is the target of the features; The adsorption of negative pressure of supplementary feeding system is abbreviated to FC1; The pressure of wind knife abbreviated to FC2; The adsorption of negative pressure of walking beam abbreviated to FC3; The adsorption of negative pressure of CCD platform abbreviated to FC4; The adsorption of negative pressure of the robot abbreviated to FC5; The edge detection (left/right/up/down) abbreviated to FC6-9; The angle detection abbreviated to FC10; The rollover test of 180°abbreviated to FC11.

TABLE 8. The sample 1.

	FC1	FC2	FC3	FC4	FC5	FC6	FC7	FC8	FC9	FC10	FC11
sp 1	0.21	-43.4	-18.5	-69.1	-38.8	11	44	41	38	41	9

Take FC1 as an example to calculate the SNR:

$$\eta_1 = 10\lg\frac{\mu^2}{\sigma^2} = 10 \times \lg\frac{0.205^2}{0.000488} = 19.35033$$

The weight of FC1 is calculated by using equation (2) as:

$$\begin{aligned}\lambda_1 &= \frac{\frac{1}{\eta_1}}{\sum_{j=1}^{n}\frac{1}{\eta_j}} \\ &= \frac{\frac{1}{19.35}}{\frac{1}{19.35}+\frac{1}{22.01}+\frac{1}{27.47}+\frac{1}{27.06}+\frac{1}{15.88}+\frac{1}{23.19}+\frac{1}{22.48}+\frac{1}{22.43}+\frac{1}{22.32}+\frac{1}{22.94}+\frac{1}{9.71}} \\ &= 0.003906\end{aligned}$$

Take sample 1(abbreviated to sp1) as an example to measure the features in TABLE 8:

The quality loss of feature 1 of sample is calculated as:

$$L_1(y_1) = \left(\frac{y_1 - T_1}{T_U^1 - T_l^1}\right)^2 = \left(\frac{0.21-0.215}{0.25-0.17}\right)^2 = 0.00390625$$

Calculate the Fragmentation Characteristic Quality Loss (FCQL) of each feature in sp1 in TABLE 9:

Calculate the multi-feature quality loss of sp1 based on SNR by using equation (4):

$$\begin{aligned}L(y_1, y_2, \ldots y_{11}) &= \sum_{i=1}^{11}\lambda_i L(y_i) \\ &= 0.0928 \times 0.003906 + \ldots + 0.184846 \\ &\quad \times 0.001736 = 0.0172\end{aligned}$$

TABLE 9. The fragmentation characteristic quality loss (FCQL) of sample 1.

	FC1	FC2	FC3	FC4	FC5	FC6	FC7	FC8	FC9	FC10	FC11
FCQL	0.003906	0.008858	0.015625	0.006574	0.002975	0.04	0.111111	0.006944	0.033058	0.006944	0.001736

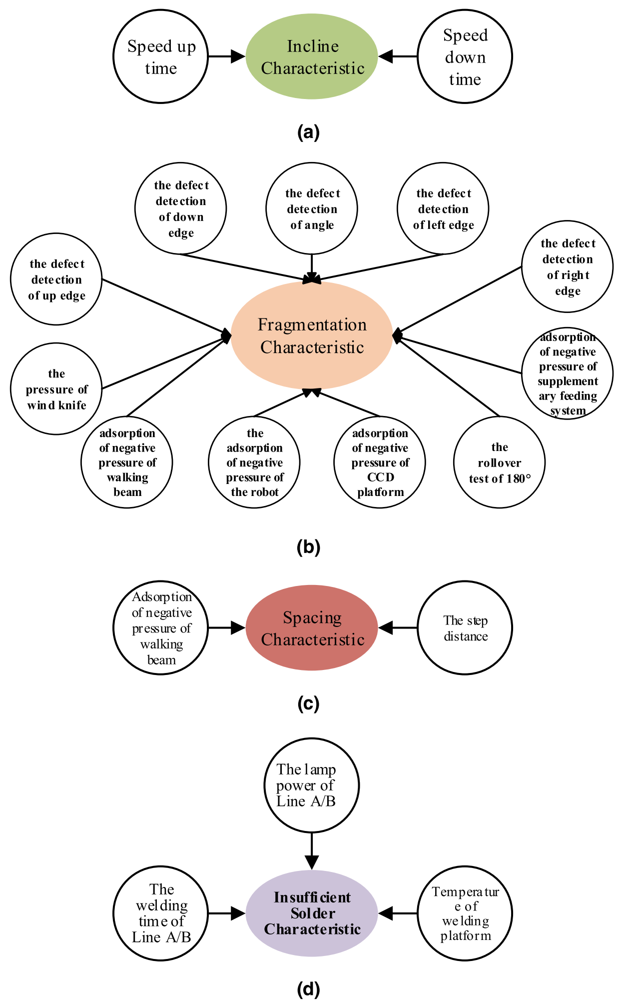

FIGURE 5. The Welding Unit-Level of the solar cell production line. a) The feature set of Incline Characteristic. b) The feature set of Fragmentation Characteristic. c) The feature set of Spacing Characteristic. d) The feature set of Insufficient Solder Characteristic.

C. THE THRESHOLD

For the 216 samples collected in the production line, the quality loss of the Fragments Characteristic are measured and sorted, as shown in the TABLE 10:

According to the engineering practice, the fragment samples are 206 /202/205/213/205/213/210/215/201/214/209/212/209/212, whose range of FCQL is [0.128339, 0.2322]. The threshold is set to 0.128339. The FCQL below the threshold is fragmentation characteristic normal and the above or equal is broken (Abnormal).

According this method, other features can be measured, and the quality loss value is used as the basis for fault discovery and provides decision support. The TABLE 11 is the feature measurement of Incline/Insufficient Solder/Spacing Characteristic and the TABLE 12–14 are the quality loss of the three characteristic.

According to the engineering practice, the incline samples are199/210/211/202/203/212, whose range of ICQL is [0.238828, 0.293457].The threshold is set to 0.238828. The ICQL below the threshold is incline characteristic normal and the above or equal is incline (abnormal).

According to the engineering practice, the insufficient solder samples are 205/200/206/199/203/211/215/208, whose range of ISCQL is [0.380776, 0.555894].The threshold is set to 0.380776. The ISCQL below the threshold is insufficient solder characteristic normal and the above or equal is insufficient solder (abnormal).

According to the engineering practice, the spacing samples are 204 /214/203/213/211/202/208/215, whose range of SCQL is [0.178937, 0.221521].The threshold is set as 0. 178937. The SCQL below the threshold is spacing characteristic normal and the above is abnormal.

IV. CASE STUDY OF UNIT-LEVEL AND SYSTEM-LEVEL

In the previous chapter, this paper analyzes quality loss measurement and the fault discovery of the Characteristic-Level(fragmentation/incline/insufficient solder/spacing characteristic). This section from the Unit-Level and System-Level, will calculate the quality loss and the fault discovery by abnormal feature selection and feature measurement based on the QLF-SNR.

A. ABNORMAL FEATURE SELECTION OF UNIT-LEVEL AND SYSTEM-LEVEL BASED ON RELIEF

Take the Welding Unit-Level as an example. There are quite more features, including the features belong to the fragmentation, incline, insufficient solder, spacing characteristic and some other features, which cannot be classified into the above four characteristics, as shown in the below FIGURE 6:

According the mechanical structure, the feature set can be described 14 Sub-Units as the TABLE 15. A total of 309 dimension features can be collected.

The weight accumulative value and correlation coefficient is set to 2500 and 0.95 respectively. The Relief based on Mahalanobis Distance for feature selection gets 11 dimensions features: the welding time of A/B production line(Feature-Unit-Level 11 shown in TABLE 16 abbreviated to FU11), the adsorption of negative pressure of supplementary feeding system(abbreviated to FU1),the adsorption of negative pressure of CCD platform(abbreviated to FU2),the adsorption of negative pressure of the robot

TABLE 10. The quality loss of fragmentation characteristic (FCQL).

sp	FC1	FC2	FC3	FC4	FC5	FC6	FC7	FC8	FC9	FC10	FC11	FCQL	Fault
212	0.25	-34.2	-21.6	-65.7	-32.6	11	34	45	46	35	23	0.2322	Y
207	0.17	-35.5	-21.7	-65.2	-29	12	46	36	46	36	20	0.228055	Y
216	0.17	-40.5	-18	-65.6	-30.8	12	46	45	44	46	23	0.203798	Y
209	0.24	-44.2	-21.9	-76.1	-30.5	12	46	34	46	46	2	0.197126	Y
214	0.25	-50.7	-21.8	-65.4	-50.2	12	34	45	44	35	1	0.188586	Y
201	0.17	-50.9	-21.5	-76.1	-50.5	11	45	44	43	35	0	0.186993	Y
215	0.25	-50.1	-21.6	-74.3	-29	11	34	39	46	36	19	0.171892	Y
210	0.25	-50.9	-21.5	-74.8	-29.5	9	37	36	35	46	1	0.169484	Y
200	0.17	-49.6	-18.1	-65.6	-30.2	11	46	45	36	46	19	0.163771	Y
199	0.25	-49.8	-18	-66	-49.5	11	45	35	46	46	1	0.158161	Y
213	0.24	-42	-19.9	-74.6	-50.5	12	39	34	35	46	0	0.154801	Y
204	0.18	-51	-21.9	-76.2	-35.1	10	37	41	46	45	2	0.149685	Y
205	0.25	-40.2	-18.2	-74.8	-29	11	35	35	35	37	17	0.133628	Y
202	0.2	-34	-18.6	-71.2	-40.5	10	37	34	46	45	1	0.128369	Y
206	0.23	-43.4	-19.8	-69.5	-51	12	34	36	44	35	19	0.128339	Y
40	0.25	-41.1	-18.9	-66.9	-49.7	10	35	36	41	45	0	0.121366	N
…	…	…	…	…	…	…	…	…	…	…	…	…	…

Abnormal: Y; Normal: N

TABLE 11. Features measurement of Incline/Insufficient Solder/Spacing Characteristic.

	Incline		Insufficient Solder			Spacing	
	IC1	IC2	ISC1	ISC2	ISC3	ISC1	ISC2
T_i	950	150	90	1750	190	-40	158.5
T_U^i	2050	201	100	2996	215	-30	159.5
T_L^i	102	98	70	1529	180.1	-51	158.3
σ^2	330546.8	835.7674	49.58499	192326.9	53.43669	35.75271	0.003842
μ	992.5	126	93.5	1701.5	197.95	-41.65	158.545
η_i	4.74228	12.78656	22.46273	11.77624	28.65271	16.85921	68.15735
λ_i	0.729458	0.270542	0.270898	0.516728	0.212375	0.801695	0.198305

Speed up time of traction servo deceleration is abbreviated to IC1; Speed down time of traction servo deceleration is abbreviated to IC2; The lamp power of Line A/B is abbreviated to ISC1; The welding time of Line A/B is abbreviated to ISC2; The temperature of welding platform is abbreviated to ISC3; The adsorption of negative pressure of walking beam is abbreviated to SC1; The step distance is abbreviated to SC1;

TABLE 12. The quality loss of incline characteristic (ICQL).

sp	IC1	IC1 Quality Loss	IC2	IC2 Quality Loss	ICQL	Fault
212	2050	0.318865	98	0.254878	0.293457	Y
203	2020	0.30171	200	0.235649	0.275478	Y
202	2010	0.296097	201	0.245169	0.275874	Y
211	1986	0.282841	99	0.245169	0.267882	Y
210	2035	0.310228	186	0.12216	0.235549	Y
199	1930	0.25309	198	0.217174	0.238828	Y
63	1947	0.261946	108	0.166274	0.223956	N
…	…	…	…	…	…	…

Abnormal: Y; Normal: N

(abbreviated to FU3),the adsorption of negative pressure of walking beam(abbreviated to FU4),the angle detection (abbreviated to FU5),the edge detection(left/right/up/down, abbreviated to FU6/FU7/FU8/FU9 respectively)and the rollover test of 180 is FU10.(Ordered by weight).

B. THE UNIT-LEVEL QUALITY LOSS MEASUREMENT AND FAULT DISCOVERY BASED ON QLF-SNR

The following TABLE 16 shows the 11 dimensions features of Unit-Level and the parameters of the Taguchi method. And for the 216 samples, the quality loss of Welding

TABLE 13. The quality loss of insufficient solder characteristic (ISCQL).

sp	ISC1	ISC1 Quality Loss	ISC2	ISC2 Quality Loss	ISC3	ISC3 Quality Loss	ISCQL	Fault
208	71	0.401111	2992	0.716775	213.5	0.453404	0.555894	Y
215	72	0.36	2986	0.709867	209.7	0.318626	0.508576	Y
211	76	0.217778	2948	0.666889	214.3	0.484799	0.482551	Y
203	77	0.187778	2955	0.674705	213.2	0.441901	0.466661	Y
199	71	0.401111	2943	0.661334	180	0.082101	0.444945	Y
206	73	0.321111	2924	0.640436	182.3	0.048678	0.402435	Y
200	79	0.134444	2995	0.720242	180.1	0.080467	0.386751	Y
205	74	0.284444	2897	0.611317	181.3	0.062142	0.380776	Y
86	97	0.054444	2995	0.720242	184.1	0.028579	0.349416	N
…	…	…	…	…	…	…	…	…

Abnormal: Y; Normal: N

TABLE 14. The quality loss of spacing characteristic (SCQL).

sp	SC1	SC1 Quality Loss	SC2	SC2 Quality Loss	SCQL	Fault
215	-51	0.274376	158.38	0.01	0.221521	Y
208	-50.9	0.26941	158.59	0.005625	0.216673	Y
202	-50.5	0.25	158.58	0.004444	0.200907	Y
211	-50.4	0.245261	158.35	0.015625	0.199351	Y
213	-50.2	0.235918	158.35	0.015625	0.191876	Y
203	-50.1	0.231315	158.55	0.001736	0.185417	Y
214	-50.1	0.231315	158.54	0.001111	0.185292	Y
204	-50	0.226757	158.35	0.015625	0.184547	Y
69	-49.9	0.222245	158.41	0.005625	0.178937	N
…	…	…	…	…	…	…

Abnormal: Y; Normal:N

TABLE 15. The welding unit-level features in 14 sub-unit.

System	Features and Numbers
Preparation Process Sub-Unit	Belt/Flux/ The pressure of wind knife /Servo reset/reset or not, etc. 43 items in total.
Feeding Sub-Unit	The number of feeding cells/Step forward or backward/ Step distance, etc. 13 items in total.
Loading Sub-Unit	Status of suction fan / The grab position of cells in Loading Unit / Cylinder waiting position, etc. 18 items in total.
CCD Vision Sub-Unit	Number of NG cells / Battery plate specifications / Edge detection / Grid line detection, etc. 66 items in total.
Manipulator Transfer Sub-Unit	Reset button / ROB connection status / The grab position of CCD platform/ The distance from battery box to the adjust platform /The distance from the adjust platform to the CCD platform, etc. 20 items in total.
Release System Sub-Unit	The continuous welding traction force / Tension tightened state, etc. 8 items in total.
Pressure Belt Sub-Unit	Fault status / The enable status of welding band bending / The power of bending cylinder, etc. 7 items in total.
Cutting Mechanism System Sub-Unit	Tape Length of solder strip / The blank state and length of the solder strip head and tail / Number of cells / Cut-and-Hold State, etc. 18 items in total.
Welding Platform Sub-Unit	The state and temperature of the heat preservation / cooling, etc. 15 items in total.
Photovoltaic Welding Sub-Unit	Real-time production / Welding temperature / Traction jaw / Welding time / Conveyor speed, etc. 25 items in total.
Film System Sub-Unit	Film material selection / Clamp force of the film / Platform temperature conditions, etc. 12 items in total.
Lateral Transfer Sub-Unit	Lateral movement state / Full number of NG box / Finished box full inspection, etc. 11 items in total.
Flip Mechanism Sub-Unit	Transport state / Adsorption mechanism state / Adsorption flip state, etc. 9 items in total.
To be Classified	Discharge OK / NG inspection / Cumulative capacity / Welding frequency / Number of welding / The number of NG / Beat time / Welding light power, etc. 44 items in total.

Unit-Level(WUQL) is measured and sorted as shown in the TABLE 17:

According to the engineering practice, the welding abnormal samples are 208/202/205/211/204/206/200/199/201/210/215/213/214/207/209/216/212/203, whose range of WUQL is [0.118236, 0.242307].The threshold is set to 0.118236. The WUQL below the threshold is welding normal and the above or equal is abnormal.

TABLE 16. The measurement of welding unit.

	FU1	FU2	FU3	FU4	FU5	FU6	FU7	FU8	FU9	FU10	FU11
T_i	-45	-19	-70	-40	10	40	40	40	40	10	2250
T_U^i	-34	-18	-65.1	-29	12	46	45	46	46	24	2996
T_L^i	-51	-22	-76.2	-51	9	34	34	35	35	0	1529
σ^2	10.64378	0.632643	9.608537	39.20544	0.528488	9.492829	9.356568	10.33796	10.05889	42.71697	192326.9
μ	-42.25	-19.3	-72.9	-41.4	9.5	37.5	37.5	41	42	12.5	2033.5
η_i	22.24557	27.69956	27.42798	16.40654	22.32412	21.70667	21.76946	22.11133	22.43948	5.632196	13.32448
λ_i	0.068353	0.054895	0.055438	0.09268	0.068113	0.07005	0.069848	0.068768	0.067762	0.269976	0.114117

TABLE 17. The quality loss of the welding unit(WUQL).

sp	FU1	FU2	FU3	FU4	FU5	FU6	FU7	FU8	FU9	FU10	FU11	WUQL	Fault
212	-34.2	-21.6	-65.7	-32.6	11	34	45	46	35	23	1643	2423	Y
216	-40.5	-18	-65.6	-30.8	12	46	45	44	46	23	1629	2243	Y
209	-44.2	-21.9	-76.1	-30.5	12	46	34	46	46	2	2754	2157	Y
207	-35.5	-21.7	-65.2	-29	12	46	36	46	36	20	2087	2146	Y
214	-50.7	-21.8	-65.4	-50.2	12	34	45	44	35	1	1634	2074	Y
213	-42	-19.9	-74.6	-50.5	12	39	34	35	46	0	1712	1837	Y
215	-50.1	-21.6	-74.3	-29	11	34	39	46	36	19	2986	1826	Y
210	-50.9	-21.5	-74.8	-29.5	9	37	36	35	46	1	1561	1798	Y
201	-50.9	-21.5	-76.1	-50.5	11	45	44	43	35	0	1712	1778	Y
199	-49.8	-18	-66	-49.5	11	45	35	46	46	1	2943	1716	Y
200	-49.6	-18.1	-65.6	-30.2	11	46	45	36	46	19	2995	1710	Y
206	-43.4	-19.8	-69.5	-51	12	34	36	44	35	19	2924	1683	Y
204	-51	-21.9	-76.2	-35.1	10	37	41	46	45	2	1651	1477	Y
211	-49.3	-18	-74.9	-43.9	10	39	38	42	41	24	2948	1449	Y
205	-40.2	-18.2	-74.8	-29	11	35	35	35	37	17	2897	1398	Y
202	-34	-18.6	-71.2	-40.5	10	37	34	46	45	1	1937	1326	Y
208	-44.7	-19.7	-74.6	-33.3	11	43	34	38	36	19	2992	1309	Y
74	-46.6	-19.4	-73.7	-49.9	9	35	36	39	37	0	1612	1291	N
203	-40.7	-22	-66.1	-36.4	10	42	44	35	43	4	2955	1182	Y

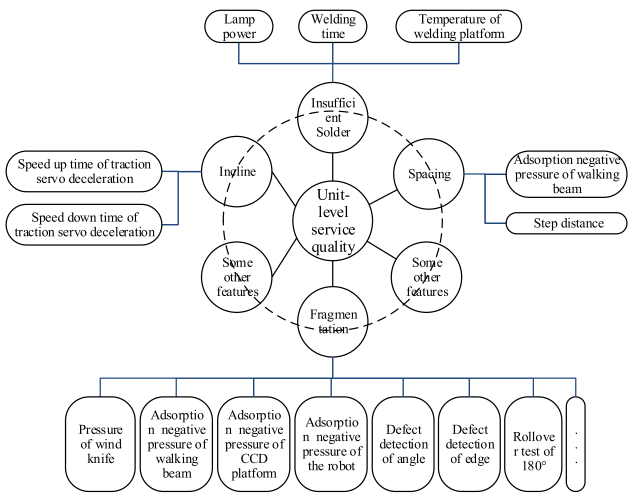

FIGURE 6. The welding Unit-Level features.

C. ACCURACY TEST

According to this method, the quality loss of each sample is calculated and marked as the calibration value. Based on some lower dimensions selected features, the threshold has been set, and the accuracy of different-dimensions with different-method is obtained as the following TABLE 18:

TABLE 18. The accuracy of different-dimensions with different- method.

	Relief based on Mahalanobis Distance	Relief based on Euclidian Distance	Fisher
Recognition of 5 dimensions	96.20%	96.62%	96.81%
Recognition of 6 dimensions	96.90%	97.41%	97.31%
Recognition of 7 dimensions	97.73%	97.82%	97.73%
Recognition of 8 dimensions	98.19%	98.24%	97.87%
Recognition of 9 dimensions	97.92%	97.27%	98.43%
Recognition of 10 dimensions	98.70%	98.66%	98.24%
Recognition of 11 dimensions	99.54%	98.66%	98.75%
Recognition of 12 dimensions	99.55%	99.54%	98.80%
Recognition of 13 dimensions	99.54%	99.55%	99.54%
Recognition of 14 dimensions	99.55%	99.56%	99.55%
Recognition of 15 dimensions	99.56%	99.56%	99.58%
Recognition of 16 dimensions	99.56%	99.55%	99.63%

As shown in TABLE 18, it is obvious that the accuracy of the Relief algorithm based on Mahalanobis Distance for 11 ∼ 16 (and even higher) dimensional features, is keeping above 99.5%, and the range of variation is quite small. Whereas the accuracy over 99.5% of Relief based on Euclidian Distance starts from 12 dimensions and the Fisher's algorithm starts from 13 dimensions.

Therefore, from the perspective of the algorithm accuracy and feature extraction efficiency, the Relief based on Mahalanobis Distance for 11-dimensional feature selection is the best.

V. CONCLUSION

The contribution of this paper can be summarized as follows:

(1) This study introduces the multi-level coordination welding quality fault discovery of an intelligent production line by using QLF-SNR. By calculating the deviation degree of the quality features and making the threshold to distinguish the abnormal and normal samples, this method makes the fault discovery more targeted which can reduce the noise interference and improve the accuracy of the discovery to some extent. A case study has been test the method, the 11 dimensions with accuracy over 99.5% Relief based on Mahalanobis Distance is chosen. And the threshold of theUnit-Level and 4 Characteristic-Level are:

[0.118236, 0.128339, 0.238828, 0.380776, 0. 178937]

(2) While the threshold of fault is just one application of this method, and the quality loss values under the threshold can be classified into different types to evaluate the welding quality of normal welding cells. In one word, the deviation degree of the quality features is measured by this method.

It could be interesting to do the future study on machine learning of the evaluation of the welding quality and self-adaption:

(1) How to deal with the deviation degree of the quality features by evaluating the welding quality by using some deep learning algorithm.

(2) Prediction analysis accomplishes beforehand the fault to self-adapt in the welding-driven platform.''

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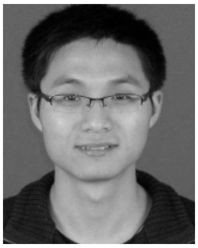

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