SMART SYSTEM FOR LOCATING SURFACE DEFECTS ON STEEL STRIPS USING SVD

Final Year UG Project Report

Submitted in Partial Fulfillment of the Requirements for the Degree of

Bachelor of Technology (Mechanical Engineering)

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Date of submission:17-05-23

FORWARDING

I hereby forward the thesis entitled “ ***Smart system for locating surface defects on steel strips using SVD****”, submitted by Jagriti Garg, Kanchan Bharti, Voleti Dharma Nandana Rajkumar, and Alok Singh, here under my guidance and supervision in partial fulfillment of the requirements for the degree of* ***Bachelor of Technology*** *in* ***Mechanical Engineering*** *in the Department of Mechanical Engineering, Indian Institute of Engineering Science and Technology, Shibpur.*

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CERTIFICATE OF APPROVAL

The foregoing progress report is hereby approved as a creditable study of Engineering subject carried out and presented in a satisfactory manner to warrant its acceptance as a prerequisite for the Degree of **'Bachelor of Technology** in **Mechanical Engineering** in the Department of Mechanical Engineering, Indian Institute of Engineering Science and Technology, Shibpur for which it has been submitted. It is understood that by this approval the undersigned does not necessarily endorse or approve any statement made, opinion expressed, or conclusion drawn therein but approves the thesis only for the purpose for which it has been submitted.

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ACKNOWLEDGMENT

We would take the opportunity to express our sincere respect, thanks, and deep gratitude to our respected project guide **Dr. Partha Pratim Dey,** Professor, Department of Mechanical Engineering, Indian Institute of Engineering Science and Technology, Shibpur, Howrah-711103, for his precise technical guidance. This final year project progress report would never have been completed without his constant help and encouragement, untiring perseverance which is underlying in the procedures, as well as the relevant steps formulated by us. The blessing, help, and guidance given by him from time to time shall carry us a long way in the journey of life.

We also take this opportunity to express a deep sense of gratitude to the Head of the Department for giving us the chance to work on such a project and encouraging us at every stage of our endeavor.

We would also like to put on record our acknowledgment of all those persons who came forward with helpful suggestions during the course of our project.

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1. ABSTRACT

This report presents **a smart system for locating surface defects on steel strips using the Singular Value Decomposition (SVD)** method. Detecting surface defects is critical in ensuring product quality and safety in the manufacturing industry. However, traditional methods for defect detection can be time-consuming and expensive, as they require complex image segmentation algorithms. The proposed system works by projecting the gray level matrix of a digital image onto its singular vectors, obtained through SVD. Defects on the steel strip are reflected as sudden changes in the projections, allowing for their prediction and location. The system does not require image segmentation and can accurately predict and locate surface defects with ease. The experimental results demonstrate the validity and effectiveness of the proposed system in detecting surface defects on steel strips. The system offers several advantages over traditional image segmentation methods, including increased efficiency, ease of implementation, and greater accuracy. The experimental results demonstrate the effectiveness of the proposed system in detecting surface defects on steel strips, highlighting its potential for use in the manufacturing industry.

2. INTRODUCTION

Steel strips are an essential material used in various industries such as machinery, aerospace, and electronics. The quality of the surface of these steel strips plays a crucial role in their performance. However, during their production, different types of surface defects may occur due to the limitations of the production process and the physical and chemical properties of the steel. These defects not only affect the appearance of the steel strips but also their performance, including their resistance to wear, corrosion, and fatigue. Moreover, such defects can lead to significant economic losses, waste of resources, and even safety hazards if not detected and addressed effectively.

In India, where the steel industry faces overcapacity, it is even more crucial to detect surface defects in steel strips as they can cause significant damage to the economy and society. Therefore, detecting and controlling surface defects in steel strips is an essential part of the quality control process to ensure their performance and safety.

Digital image processing has become a popular approach to detecting surface defects in products. Different algorithms have been developed for feature extraction and identification of these defects, and they can be broadly categorized into three types: statistical methods, frequency spectral methods, and model-based methods.

Statistical methods involve using statistical properties such as the statistical histogram [1] and gray-level cooccurrence matrix to identify defects. Additionally, morphological operations can also be used in these methods.

Frequency domain methods involve Fourier analysis, Gabor transforms, and wavelet analysis to extract features from the image and identify defects.

Model-based methods are focused on using fractal geometry [2] to detect and classify surface defects.

All these methods have been used successfully in detecting surface defects, and their effectiveness depends on the type and characteristics of the defects being detected. The choice of the most suitable method for a particular application depends on the specific requirements and constraints of the problem at hand.

Various computer vision methods have been developed to detect surface defects in steel strips, utilizing the algorithms mentioned above. However, each method has its own strengths and limitations.

Statistical methods are useful in determining the presence of defects without the need for image segmentation, but they are less effective in identifying the exact location of the defect.

Frequency spectral methods are effective in detecting defects in the frequency domain, but they require complex transformations from the spatial domain to the frequency domain.

Model-based methods are based on fractal geometry and can be useful in detecting and classifying surface defects, but they lack a standardized modeling method, making it challenging to establish the model accurately.

In summary, each method has its own set of advantages and constraints, and choosing the appropriate method depends on the specific requirements and constraints of the application at hand.

Steel is an essential component in many industrial processes, and the quality of the steel is paramount to the success of those processes. Surface defects in steel strips can have a significant impact on the quality of the finished product and may even result in the failure of the product. Therefore, detecting and predicting surface defects in steel strips is crucial for ensuring the quality of the final product.

Traditional inspection methods for surface defects on steel strips are time-consuming, labor-intensive, and prone to human error. With the advancements in computer vision and artificial intelligence, the use of machine learning and image processing algorithms has become popular in detecting and predicting surface defects in steel strips. Image segmentation, a technique used in image processing, has been widely used for detecting surface [3] defects on steel strips. However, image segmentation algorithms are often complex and may not always accurately identify the defects.

This report presents a novel approach for **locating surface defects on steel strips using Singular Value Decomposition (SVD)**. SVD is a matrix decomposition method that has been used in various fields, such as data compression, signal processing, and image analysis.The proposed system works by projecting the gray level matrix of a digital image onto its singular vectors, obtained through SVD. Defects on the steel strip are reflected as sudden changes in the projections, allowing for their prediction and location.

The proposed method has several advantages over traditional image segmentation techniques:

- **Firstly**, it does not require a complex image segmentation algorithm, reducing the computational complexity and increasing the efficiency of the process.
- **Secondly**, the proposed method can detect surface defects that may not be visible to the naked eye.
- **Finally**, the method is flexible and can be applied to different types of surface defects, making it a versatile approach for surface defect detection and prediction in the steel industry.

The proposed system has numerous applications in the manufacturing industry, including steel production, metalworking, and fabrication. By improving the accuracy and efficiency of surface defect detection, the system can significantly improve the quality and safety of steel products, while reducing costs and increasing productivity.

The remainder of the report is organized as follows. Section 4 provides a detailed description of the SVD-based approach to detecting and locating surface defects on steel strips. Section 7 presents the experimental results, demonstrating the effectiveness of the proposed method in detecting and predicting surface defects on steel strips. Section 11 concludes the paper, by highlighting the contributions of the proposed method and suggesting future research directions.

3. LITERATURE REVIEW

- **CHANG Yu-qing et al. (2010)** presented a Windows-mean MPLS to predict strip quality in continuous annealing processes. Based on the corresponding window width determined by the time span of each furnace strip, MPLS was suggested to run on the variable mean trajectories to predict the quality. They showed that it solves the problem of data redundancy and complexity of model structure and the limitations of traditional MPLS methods in dealing with data of unequal length. Experiments confirm its effectiveness and can be extended to cases similar to the continuous annealing process.

- **Jong-Moon Ha et al. (2021)** have presented an end-to-end autoencoder-grounded ultrasonic testing system able to linearly prognosticate the depths of sub-surface blights in touch with UT. Pure normal signals were measured from undistorted instances and pseudo-normal concatenated by pre-trained autoencoders to address non-uniform ultrasonic inspection conditions that can affect signal properties Using signals, a two-step training method was proposed by them. For this purpose, a rational threshold system using a Gaussian mixture model of mean absolute differences (Birse) from pre-trained autoencoders was used. Pseudo-normal signals were often used to train models to improve their performance. Pre-trained autoencoders were validated to roughly reveal distortion-related echo signals that were not detected by conventional approaches due to dominant clutter. Moreover, the alternative training method further improved the standard of appearance-related function by adaptively incorporating conventional behavior in recently measured ultrasound signals. Despite the promising performance of the proposed system, it needed further validation using colorful types of samples and spoilage that can fully demonstrate the investigation conditions for NDT in the field. Furthermore, a comprehensive study of the hyperactivity parameters, and thus the number of bumps in the autoencoder, and more advanced deep literacy models or inference systems are often performed to improve the performance of the proposed system.

- **Niclas Ståhl et al. (2019)** have presented the case of detecting a steel plate with a high risk of being telescoped during hoisting using a bidirectional RNN with an LSTM cell and an attention mechanism which yielded an area under the ROC curve of 0.85. That meant, for example, that the model can detect 80% of all telescoped samples while misclassifying less than 25% of non-telescoped samples. They found that there is no similar approach to solving this problem. The performance of RNN is significantly better than that of all baseline methods considering only summary statistics of sensor readings. That demonstrated the potential benefits that can be gained from analyzing continuous raw data rather than the aggregated summary statistics that are common today. Other deep learning techniques have been used to solve other problems in the steelmaking industry, with state-of-the-art results when it comes to predicting product quality. They mentioned that it's often very difficult to interpret the reasoning of these methods, and it is often impossible to extract knowledge about a given process. In their article, they used attention mechanisms to overcome this problem. They showed how to present a way to visualize the inner reasoning of the network. Through this visualization, the algorithm can show what knowledge it has learned about the process. This knowledge is very important to fully understand the process and to determine and motivate new process improvements.

- **R. Jones (2008)** presented that the published literature, for short to medium-size cracks, does not agree with the experimental data for the approximate 2D solution of the composite repair of metal plates with cracks and that the problem considered in the presented paper indicates that fiber bridging has an impact. This is a secondary effect that can often be ignored for practical purposes. Therefore, structures repaired using glare patches with significantly higher interlaminar shear modulus exhibit better fatigue performance than structures repaired using boron-epoxy patches. Another finding of the study done by him was that predicting the impact of composite repairs on the structural integrity of cracked components repaired by external-bonded composite repairs was dramatically simplified and only effectively reduces the stress field within the structure.

- **Mingming Jiang et al. (2017)** proposed five types of characteristics, including texture, color, and shape. Second, a random subspace SVM classifier was proposed to overcome the overfitting problem. They then introduced a simple Bayesian to fuse the basic SVM results. Finally, they showed how to develop the classifier further. The test results showed that the Bayes kernel (BYEC) algorithm is adaptive compared to other algorithms when the steel surface defect data set is changed. Their investigation showed that the classifier fitness is strongly related to a parameter mentioned in their paper. As the parameter increases, BYEC provides a better fit, but with some loss of accuracy. They suggested that we can apply the original BYEC algorithm to the modified model without labeled patterns and that a new classifier can be trained on top of the old classifier with a small sample set to improve accuracy. Future work is to improve accuracy on both large sample sets and modified production models.

- **Vladimir Panjkovic (2007)** presented a comprehensive strip temperature prediction model for hot rolling mills that were developed, covering all important aspects of strip heat transfer. Tests using plant data and benchmark comparisons with other models in the literature confirmed the superior performance of the new model. The average absolute difference between the predicted and measured strip surface temperatures at the exit of the rolling mill was 3.1 degrees Celsius for a wide range of steel grades, strip thicknesses, and widths. Parametric sensitivity tests showed that the calculated temperature was most sensitive to deformation heat, ribbon emissivity, and ribbon heat capacity. They showed that most models in the literature ignore friction-sliding heat in the nip and heat generated by scale formation on the strip surface. However, these phenomena have been shown to have a significant effect on the calculated temperature.

- **Mengjiao Li et al. (2022)** proposed a detection algorithm based on an improved YOLOv4 In response to the multiple difficulties faced in the task of steel strip defect detection. The advantage of the algorithm is that the YOLOv4 backbone network is embedded in CBAM, the YOLOv4 feature extraction network SPP module is upgraded to a customized RFB structure, and the network is deepened. Among the four error types on the NEU-DET dataset, the model achieves a 3.87% improvement in maps over his original YOLOv4, and over current mainstream target detection networks. However, the proposed method still has some limitations. For example, its inclusion and patch detection capabilities remain rather weak, with fewer bad example images in the experimental dataset. will be further improved as they mentioned.

- **Franz Pernkopf (2004)** proposed an approach aimed at detecting three-dimensional surface defects on scale-covered steel blocks. Intensity imaging performs poorly due to the significant changes in reflection properties across flawless surfaces. To overcome this limitation, light sectioning is employed to obtain surface range images. Considering the arbitrary location of acquired sections within a few millimeters range caused by vibrations, the recovery of the depth map accounts for this factor. Classification of surface segments is carried out using Bayesian network classifiers based on a set of extracted features. The proposed approach demonstrates excellent performance in extremely harsh environments, achieving a classification success rate of over 98%. However, the system may fail if surface flaws are completely covered with scale, and the appearance of the scale depends on the steel composition, leading to potential detection challenges with different types of steel. The paper utilizes the classical sequential floating search algorithm to learn the network structure of the tree-augmented naıve Bayes network and the selective unrestricted Bayesian network classifier. This algorithm allows for the removal of previously added arcs/attributes if they are deemed irrelevant at a later stage of the search. Experiments conducted on a data set consisting of 516 surface segments demonstrate that the selective unrestricted Bayesian network classifier outperforms the tree-augmented naıve Bayes, selective naıve Bayes, and naıve Bayes classifiers. The classifier, based on a selected subset of features, achieves better results in terms of five-fold cross-validation classification accuracy estimate during structure learning and classification performance on an external hold-out data set.

➢ **Jozef Svetlík et al. (2021)** introduces an innovative predictive system for quality management in metallurgical production processes, particularly focused on sheet steel rolls. This system serves as a highly efficient tool to ensure a sophisticated production process, aiming to stay ahead of compromised quality and minimize losses caused by process imperfections. The system is integrated into existing production processes, leveraging advanced camera systems as its core components. While it can be implemented into pre-existing production lines, the ideal approach involves installing tailored support systems in newly constructed production lines, custom-designed to meet the specific requirements of the production system. The predictive quality management system described in the paper utilizes the optical properties of defects detected on the surface of the strip and employs mathematical calculations for defect classification. Presently, the defect detection and classification process primarily focuses on defects occurring during the hot-rolling process. The classification of defects on the hot-rolling mill serves as the foundation for a two-step system of defect detection and classification. Defects are classified based on their optical properties and are inspected at the pickling line exit, comparing them to the defects identified at the hot-rolling mill. By assessing whether the observed properties align with the predicted effect, it becomes possible to determine the type of defect and its impact on the product and subsequent production processes. Using the evaluation of defects, decisions are made regarding further processing or rework, with the goal of maximizing product utilization and minimizing negative effects on production equipment. The aim is to eliminate adverse events or failures in the production process. The predictive system of quality management presented in this paper combines defect detection, classification, and decision-making to ensure optimal production outcomes and mitigate the impact of defects on the production process.

➢ **Valentina Colla et al. (2011)** discusses the challenges of controlling under pickling and over pickling defects during the pickling process, which are often caused by a lack of control over acid concentrations, solution temperature, and contact time. Traditional pickling lines rely on manual adjustments by operators, which are not always effective in achieving desired results. To address this, Colla proposes a model consisting of two units: a decision tree unit for classifying valid process windows and suggesting optimal line speeds to avoid under pickling defects, and a neuro-fuzzy model called RecBFN to predict under pickling defects based on unbalanced datasets. By combining these units, the model predicts the maximum line speed or speed range to prevent under pickling defects, providing operators with guidance for optimal conditions and quality improvement while reducing costs. The model can be adapted for different line types through retraining. Future work involves extending the model to detect over pickling defects and improving its ability to handle imbalanced classes.

- **G. Moradi et. al. (2012)** presents an automatic algorithm for determining skin color defects in apples using image processing techniques. The algorithm involves three stages: converting the image from RGB to the Lab* color space, extracting fruit shape using the ACM algorithm, and segmenting the image using the SHEM algorithm. Experimental results on an apple dataset demonstrate that both EM and SHEM algorithms require the same number of iterations and achieve identical segmentation results. However, the proposed SHEM algorithm exhibits faster processing time compared to the standard EM algorithm. The proposed algorithm achieves an accuracy of 91.72% for healthy pixels and 94.86% for defected ones in the acquired images. It is important to note that the methods mentioned in the introduction are supervised and applied to datasets that are not accessible in this study. In contrast, the proposed method is unsupervised. A comparison with EM-based algorithms shows similar results, but the proposed SHEM algorithm outperforms them significantly in terms of speed, being roughly 60 times faster.

- **Hong Zheng et al. (2011)** propose an adaptive neural-fuzzy inference system (ANFIS) model for the detection of bruises on Chinese bayberries. The model utilizes fractal dimension (FD) and RGB intensity values as input variables. Different types of input membership functions (MFs) were implemented in the ANFIS, with the 'gauss2mf' MF performing notably better than the others for defect inspection. The ANFIS achieved a classification accuracy of 100% for healthy fruits and 78.57% for bruised fruits, resulting in an overall correct classification rate of 90.00%. These findings demonstrate the potential of the ANFIS technique based on FD and RGB values as a valuable tool for detecting bruises not only in Chinese bayberries but also in other fruits throughout various stages of processing, storage, and distribution.

➢ **Nirbhar Neogi et al. (2014)** proposed in their study an extensive review of automated inspection methods for steel surfaces utilizing image processing techniques. The review encompassed publications spanning more than two and a half decades, shedding light on the recent advancements in this field. The following key observations were made:

- The challenging environment of a steel mill demands careful consideration in designing illumination and imaging systems. Steel surface images are prone to substantial noise caused by surface scale, vibrations, inconsistent or variable illumination, and the presence of pseudo defects. Moreover, surface defects exhibit irregular shapes, with their types and characteristics varying significantly among different mills. Furthermore, the characteristics of defects are influenced by the manufacturing conditions.
- The literature review revealed that a higher emphasis has traditionally been placed on defect detection on cold strip surfaces. However, recent attention has shifted towards surfaces of hot strips, bars, and rods. A wide range of techniques, both in the spatial and frequency domains, have been employed for defect detection. Often, combining multiple techniques has yielded valuable results. Regarding defect classification, neural networks and support vector machine-based techniques have demonstrated usefulness. Real-time operation of automated inspection systems necessitates fast image processing due to the high speeds typically encountered in flat and long steel product mills. Consequently, dedicated hardware systems with parallel processing capabilities for each camera are required.
- Comparing the outcomes of different techniques proves challenging due to the lack of a common standard in terms of images and experimental methods. This issue is further compounded by the absence of a standardized definition for defect types.

- While commercially available vision-based inspection systems for web materials have reached a high level of maturity, they require fine-tuning for specific applications. Continuous collaboration between designers and users is crucial to adapt the installed systems to accommodate new defect varieties or characteristics at the same site of installation.

➢ In the study conducted by **Qianlai Sun et al. (2016)**, a SVD-based method is proposed for the detection of surface defects on steel strips. This method enables convenient and accurate determination and localization of commonly encountered defects. Experimental results demonstrate a good agreement between the obtained results and the expected outcomes. The SVD-based method proves to be reliable in determining and roughly locating surface defects on steel strips. The defect detection process relies directly on image processing, eliminating the need for image segmentation or modeling. This approach offers a practical, convenient, and adequate solution for defect detection. The defect locations are initially determined using simple procedures, resulting in rough localization. However, if required, more advanced methods can be employed to ensure precise defect localization while adhering to the same underlying concept.

4. SURFACE DEFECTS ON STEEL STRIPS

Steel Strip is a steel product manufactured from a hot rolled strip and then pickled. This Steel Strip is made up of austenitic steel consisting of chromium, nickel, and manganese as the main constituents, which offers excellent thermodynamic properties such as specific heat capacity, melting point, thermal conductivity, and coefficient of linear expansion. Moreover, these steel strips are extensively used in various industries because of their main benefits like electromagnetic properties such as electrical resistivity, magnetic permeability, and electrical conductivity. Steel Strips are widely used in various industries including chemical & food processing industries, construction & building materials, automobile industries, air conditioning & refrigeration, and washer industries.

Figure 1: Steel Strip [18]

Due to the influence of raw materials, the rolling process, system control, and many other technical factors in the production process of steel strips, the surface defects such as creases, waist folding, water spots, and punching have occurred from time to time. As the raw material of machinery, aerospace, electronics, and other industries, there is a higher requirement for the surface quality of steel strips. But various surface defects occur unavoidably in the production of the steel strip constrained by its production process and physical and chemical properties.

Defects ruin not only the appearance of steel strips, but also their important performances, such as corrosion resistance, wear resistance, and fatigue strength. With defects, some steel strips are regarded as substandard or waste products in further processing. More seriously, the defects may cause significant economic losses and even safety accidents without effective defect detection.

Figure 2: Usage of Steel Strips in the Industry [18]

The surface defects of steel strips have diverse and complex features, and surface defects caused by different production lines tend to have different characteristics.

4.1 Types of Surface Defects

4.1.1. Patches

In the field of steel production, the occurrence of surface defects, such as patches and scratches, poses a significant challenge. Patches, which are irregular areas of discoloration or inconsistency on the surface of the steel, can be caused by various factors. One common cause is the presence of impurities or contaminants during the manufacturing process. These impurities can lead to uneven cooling or react with the steel surface, resulting in localized discoloration. Scratches, on the other hand, are typically caused by mechanical actions, such as contact with abrasive surfaces or mishandling during handling and transportation. These scratches can vary in depth and length, depending on the force and abrasive nature of the contact. The understanding of how these defects occur is crucial for implementing effective quality control measures and developing automated inspection methods to detect and mitigate their presence in steel products.

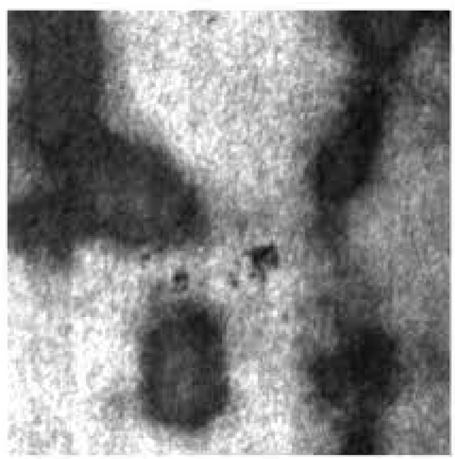


Figure 3: Patch defect [19]

4.1.2. Pitting

Pitting is another type of surface defect commonly observed in steel materials. It is characterized by small, localized cavities or depressions on the steel surface. The formation of pits can be attributed to several factors, with corrosion being the primary cause. Corrosion occurs when the steel comes into contact with corrosive agents, such as moisture, chemicals, or salts. Over time, these agents initiate a chemical reaction that leads to the degradation of the steel surface, resulting in the formation of pits. Pitting can also be accelerated by factors like high temperatures, exposure to harsh environments, or the presence of impurities in the steel composition. The severity and extent of pitting depend on the aggressiveness of the corrosive environment and the resistance of the steel alloy. Preventing and mitigating pitting requires the implementation of corrosion-resistant coatings, proper material selection, and regular inspection to detect and address any early signs of pitting before it leads to structural integrity issues.

Figure 4: Pitted Surface Defect [18]

4.1.3. Rolling

Rolling is a crucial process in steel manufacturing, where metal sheets or ingots are passed between a set of rotating rolls to reduce their thickness and shape them into desired forms. During the rolling process, various defects can occur on the steel surface. One common defect is known as rolling marks or scratches. These marks are caused by the contact between the steel surface and the rolls, resulting in localized scratches or grooves. Several factors contribute to the occurrence of rolling marks, including improper roll alignment, excessive roll pressure, insufficient lubrication, or the presence of foreign particles on the roll surface. The severity of rolling marks can range from superficial surface imperfections to deep scratches that penetrate the steel's surface. These defects not only compromise the aesthetics of the steel but can also affect its mechanical properties and performance. To minimize rolling marks, manufacturers employ techniques such as proper roll maintenance, regular cleaning of the rolls, precise alignment of the rolls, and adequate lubrication during the rolling process. Additionally, advanced monitoring and inspection systems are utilized to detect and address any rolling marks promptly, ensuring the production of high-quality steel products.

Figure 5: Rolling Defect [18]

4.1.4. Inclusion

The stainless steel strip is sometimes covered with deeply dotted black spots on the surface after pickling. It is called inclusion. It is because the iron oxide sheet is pressed into the hot rolling. Such defects cannot be taken to remove acid washing. When it is cold rolled, black spots expand and extend into the black strips, which seriously affects the impact properties of the finished stainless steel plate.

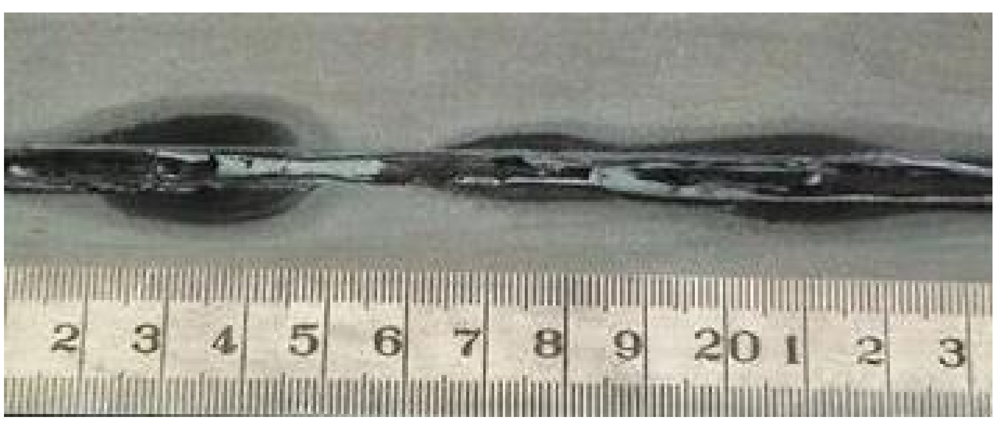


Figure 6: Inclusion defect [18]

4.1.5. Scratch

The stainless steel strip in a new unit operates in the process of scratching because foreign body hard surface drive roller, a guide roller, or stainless steel strip-shaped and folding edge and guide into the line contact, or strip in unwinding process on the folding scraper, which makes the surface draw new scars. In addition, part of the scar appeared in the process of cooling and coiling after hot rolling.

The scratch of stainless steel strips can be divided into upper surface scratch and lower surface scratch. The cold-rolled stainless steel plate will form a wide and long black strip on the surface of the finished stainless steel strip after cold rolling. Stainless steel strip scratch depth exceeds the allowable tolerance of stainless strips strip half, even after rolling cannot be eliminated.

Figure 7: Scratch defect [18]

The way to avoid scratching is to check the rolling parts and guide plates of the unit regularly and maintain the equipment well.

4.1.6. Crazing

Appearance feature: a discontinuous crack on the surface of a rolled piece, which centers on a certain point and radiates outward in the form of lightning. Depending on the extent of extension and spread, the area it affects is usually elliptical (initially circular). Cracks may also exist in the form of very small micro-cracks or hairlines. When the grain boundary is weakened by the low melting point phase (such as hot brittleness), crazing will occur. Through visual inspection, the steel plate and steel strip shall be free of cracks.

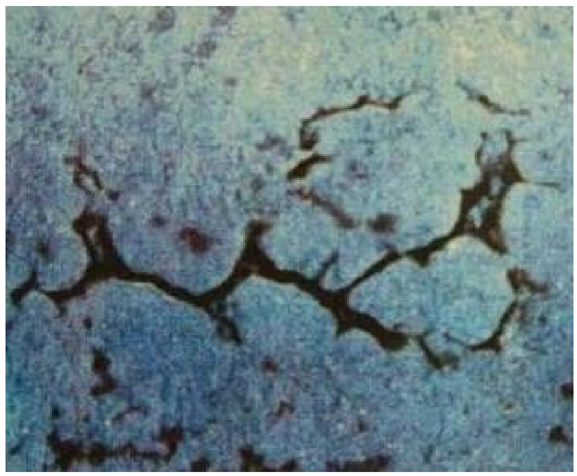


Figure 9: Crazing Defect [18]

5. SINGULAR VALUE DECOMPOSITION METHOD

The **Singular Value Decomposition (SVD)** is a powerful mathematical technique that can be used to find a lower-dimensional representation of high-dimensional data, by identifying the most important patterns that exist within the data. The SVD approach is purely data-driven, meaning that it doesn't rely on any prior knowledge or expert intuition to identify these patterns [4].

One of the main benefits of the SVD is its numerical stability, which means that small changes in the input data will result in small changes in the output, making it a reliable method for analyzing data. The SVD also provides a hierarchical representation of the data, which can be thought of as a new coordinate system defined by the dominant correlations within the data.

In addition to its stability and hierarchical representation, the SVD has another advantage over other methods such as the eigendecomposition, in that it is guaranteed to exist for any matrix. This makes it a highly versatile technique that can be applied to a wide range of data analysis problems.

In addition to its applications in the dimensionality reduction of high-dimensional data, Singular Value Decomposition (SVD) has many other powerful uses. For example, the SVD can be used to compute the pseudo-inverse of non-square matrices, which allows for solutions to underdetermined or overdetermined matrix equations such as $Ax = b$.

Another important application of the SVD is in denoising data sets. By identifying the most important patterns in the data, the SVD can effectively filter out noise and provide a cleaner and more accurate representation of the underlying signal.

Furthermore, the SVD is crucial for characterizing the input and output geometry of a linear map between vector spaces. This can be useful in a wide range of applications, such as signal processing, image analysis, and machine learning.

5.1 Definition of the SVD

Consider a large data set $\mathbf{X} \in \mathbb{C}^{n\times m}$:

$$\mathbf{X} = \begin{bmatrix} | & | & & | \\ \mathbf{x}_1 & \mathbf{x}_2 & \cdots & \mathbf{x}_m \\ | & | & & | \end{bmatrix}. \qquad (1.1)$$

The columns $\mathbf{x_k} \in$ Cn represent images that have been reshaped into column vectors with as many elements as pixels in the image.

The index k is a label indicating the k^{th} distinct set of measurements.

The columns are often called *snapshots,* and m is the number of snapshots in **X.** For many systems n>>m, resulting in a *tall-skinny matrix*, as opposed to a *short-fat matrix* when n<<m.

The SVD is a unique matrix decomposition that exists for every complex-valued matrix

$X \in \mathbb{C}^{n\times m}$:

$$\mathbf{X} = \mathbf{U\Sigma V}^* \qquad (1.2)$$

where $\mathbf{U} \in \mathbb{C}^{n\times n}$ and $\mathbf{V} \in \mathbb{C}^{m\times m}$ are *unitary matrices* with orthonormal columns, and $\in \mathbb{R}^{n\times m}$ is a matrix with real, nonnegative entries on the diagonal and zeros off the diagonal. Here ∗ denotes the complex conjugate transpose.

When n ≥ m, the matrix has at most m nonzero elements on the diagonal, and may be written as

$$\mathbf{\Sigma} = \begin{bmatrix} \hat{\mathbf{\Sigma}} \\ \mathbf{0} \end{bmatrix}.$$

Therefore, it is possible to exactly represent **X** using the economy SVD:

$$\mathbf{X} = \mathbf{U\Sigma V}^* = \begin{bmatrix} \hat{\mathbf{U}} & \hat{\mathbf{U}}^{\perp} \end{bmatrix} \begin{bmatrix} \hat{\mathbf{\Sigma}} \\ \mathbf{0} \end{bmatrix} \mathbf{V}^* = \hat{\mathbf{U}}\hat{\mathbf{\Sigma}}\mathbf{V}^*. \qquad (1.3)$$

The full SVD and economy SVD are shown in Fig. 1. The columns of Uˆ $^{\perp}$ span a vector space that is complementary and orthogonal to that spanned by Uˆ. The columns of U are called *left singular vectors* of X and the columns of V are *right singular vectors.* The diagonal elements of $\Sigma \in C^{m\times m}$ are called *singular values* and they are ordered from largest to smallest. The rank of **X** is equal to the number of nonzero singular values.

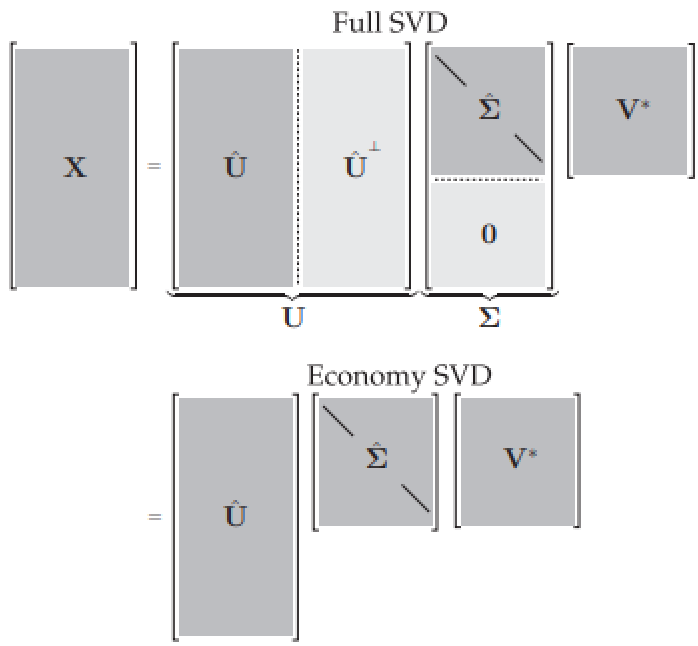


Figure 10. Schematic of matrices in the full and economy SVD [16]

5.2 Computing the SVD

The SVD is a cornerstone of computational science and engineering, and the numerical implementation of the SVD is both important and mathematically enlightening. That said, most standard numerical implementations are mature and a simple interface exists in many modern computer languages, allowing us to abstract away the details underlying the SVD computation. For most purposes, we simply use the SVD as a part of a larger effort, and we take for granted the existence of efficient and stable numerical algorithms.

In Matlab, computing the SVD is straightforward:

```
X = randn(5, 3); % Create a 5x3 random data matrix
[U, S, V] = svd(X) % Singular Value Decomposition
```

For non-square matrices X, the economy SVD is more efficient:

```
[Uhat, Shat, V] = svd(X, 'econ'); % economy sized SVD
```

6. DEFECT DETECTION METHOD BASED ON SVD

Unlike the overall background of an image in pixels, a defect can be identified as an irregular region where certain elements in the grayscale matrix display variations. The grayscale matrix consists of singular values and vectors that also change based on the elements in specific rows or columns. Consequently, the resulting vectors obtained by projecting the matrix onto its singular vectors are also affected. In the case of an image depicting a steel strip with defects, the elements of the projection vectors related to the abnormal area exhibit more significant alterations compared to those corresponding to the normal area. The sudden changes in the elements' values can be associated with specific row or column numbers, enabling the determination and approximate localization of the defect.

6.1 Defect Detection In Ideal Case

In this section, we focus on the process of determining and locating defects under ideal conditions [16]. In this ideal scenario, we assume that there is no presence of noise or interference in the grayscale image of the steel strip. In simpler terms, for an image without any defects, all the pixels have the same gray level value. Then the gray level matrix of the image can be described as

$$M = \begin{bmatrix} a & a & a & \cdots & a \\ a & a & a & \cdots & a \\ a & a & a & \cdots & a \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a & a & a & \cdots & a \end{bmatrix}_{m \times n} . \qquad (1)$$

Here, a is the grayscale of each pixel in the image.

The Singular Value Decomposition can be written in the following form:

$$A = U\Sigma V^{H} \qquad (2)$$

According to (2), there is

$$A^H A = \left(U\Sigma V^H\right)^H U\Sigma V^H = V\Sigma^H U^H U\Sigma V^H$$
$$= V\Sigma^2 V^H, \qquad (3)$$

where both U and A are unitary matrices and Σ is a diagonal matrix.

Then (3) can be expressed as

$$V^H\,(A^H A)\,V = \Sigma^2 \qquad (4)$$

In the same way, the following equation can be obtained:

$$U^H (AA^H)U=\Sigma^2 \qquad (5)$$

Thus the left singular vectors are just the eigenvectors of AA^H and right singular vectors are just the eigenvectors of $A^H A$.

The left singular vectors can be solved by eigenvalue decomposition. Then M is substituted into AA^H

$$MM^H = \begin{bmatrix} na^2 & na^2 & na^2 & \cdots & na^2 \\ na^2 & na^2 & na^2 & \cdots & na^2 \\ na^2 & na^2 & na^2 & \cdots & na^2 \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ na^2 & na^2 & na^2 & \cdots & na^2 \end{bmatrix}_{m\times m} . \qquad (6)$$

Let the eigenvalues of MM^H be λi (i = 1, 2, 3, . . . , m). Obviously, the rank of MM^H is 1, and mna^2 is the only nonzero eigenvalue of MM^H. According to eigenvalue decomposition, the eigenvalue λ_i should meet the equation $(\lambda_i I - MM^H)Ui = 0$,

$$\left(\lambda_1 I - MM^H\right)U_1 = \left(mna^2 I - MM^H\right)U_1 = \begin{bmatrix} (m-1)\,na^2 & -na^2 & -na^2 & \cdots & -na^2 \\ -na^2 & (m-1)\,na^2 & -na^2 & \cdots & -na^2 \\ -na^2 & -na^2 & (m-1)\,na^2 & \cdots & -na^2 \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ -na^2 & -na^2 & -na^2 & \cdots & (m-1)\,na^2 \end{bmatrix}_{m\times m} U_1$$

$$= na^2 \begin{bmatrix} m-1 & -1 & -1 & \cdots & -1 \\ -1 & m-1 & -1 & \cdots & -1 \\ -1 & -1 & m-1 & \cdots & -1 \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ -1 & -1 & -1 & \cdots & m-1 \end{bmatrix}_{m\times m} U_1 = 0. \tag{8}$$

As the solution of the above equation group, the vector U_1 must have the form U_1 = [bbb · · · b]1×m^H; here b is a real number. So there is

$$M^H U_1 = \begin{bmatrix} a & a & a & \cdots & a \\ a & a & a & \cdots & a \\ a & a & a & \cdots & a \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a & a & a & \cdots & a \end{bmatrix}_{m\times n}^{H} \begin{bmatrix} b & b & b & \cdots & b \end{bmatrix}_{1\times m}{}^{H} \tag{9}$$

$$= \begin{bmatrix} mab & mab & mab & \cdots & mab \end{bmatrix}_{1\times m}{}^{H}.$$

Here $M^H U_1$ is called the projection on the first left singular vector of M. In the same case, all elements of vector MV_1 are the same real number too. The vector MV_1 is called the projection on the first right singular vector of M. By using the same method, the projection vectors, both $M^H U_2$ and MV_2, are zero vectors.

According to the matrix perturbation theory, the singular values of a matrix are of good stability [5], and so are the singular vectors. In an image of the strip with defects, the projection corresponding to the defect is different from that corresponding to the normal areas.

6.2 Procedure for locating defects in real cases

The main procedures are summarized as follows:

1. Convert the color image of the steel strip into a grayscale image, resulting in the formation of a grayscale matrix.

2. Apply Singular Value Decomposition (SVD) to calculate the left and right singular vectors of the grayscale matrix. These vectors are represented as "left_vec" and "right_vec" respectively.

3. Project the grayscale matrix and its transpose onto the second right and left singular vectors, referred to as "right_vec" and "left_vec" respectively. This process yields the left and right projection vectors, denoted as "left_proj" and "right_proj":
   left_proj = Matrix multiplication of transpose of a grayscale matrix with left_vec
   right_proj = Matrix multiplication of the grayscale matrix with right_vec.

4. Calculate the absolute values of the vectors left_proj and right_proj, denoted as left_abs and right_abs respectively.

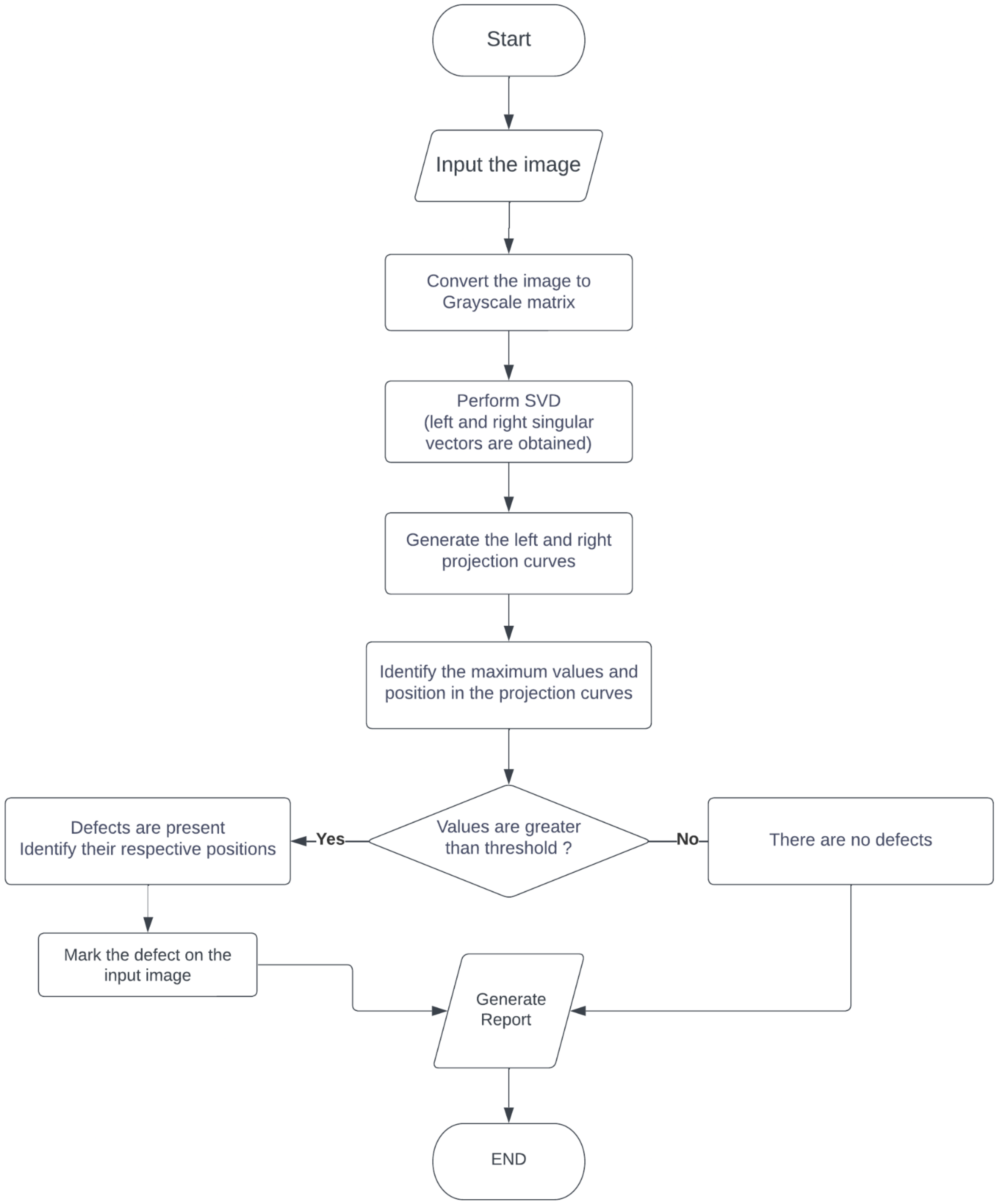
5. Find the maximum values and positions of the projection vectors.

6. Set a suitable threshold (for our data, it is **100**, discussed in detail in **section 6.3**) and determine defects using the following steps:
   (a) If both maximum values are below the threshold, there are no defects in the image.
   (b) If at least one of the maximum values exceeds the threshold, defects are present.

7. If defects are detected in the image, compare the elements of left_abs and right_abs with the threshold. Create vectors left_peak_locs and right_peak_locs containing the indexes of the elements that exceed the threshold.

8. Based on the indexes obtained, mark the defects on the input image to roughly locate the defects.

6.3 Algorithm



6.4 Determining Threshold

The threshold value in SVD method for defect detection is important because it determines how the singular values are used to identify defects. A high threshold value will result in a small number of singular values being used, which may not be enough to accurately identify defects. A low threshold value will result in a large number of singular values being used, which may lead to false positives. The optimal threshold value will vary depending on the specific image and the type of defect being detected.

Here are some of the factors that can affect the optimal threshold value:

- The size of the defect. Larger defects will be easier to detect than smaller defects.
- The contrast between the defect and the background. A high-contrast defect will be easier to detect than a low-contrast defect.
- The noise level in the image. A noisy image will make it more difficult to detect defects.

We have automated our algorithm to run over a dataset of 1800 images which includes different types of defects and appended the maximum peak value from each image into a text file. Now using these values we have plotted a graph which can be seen below.

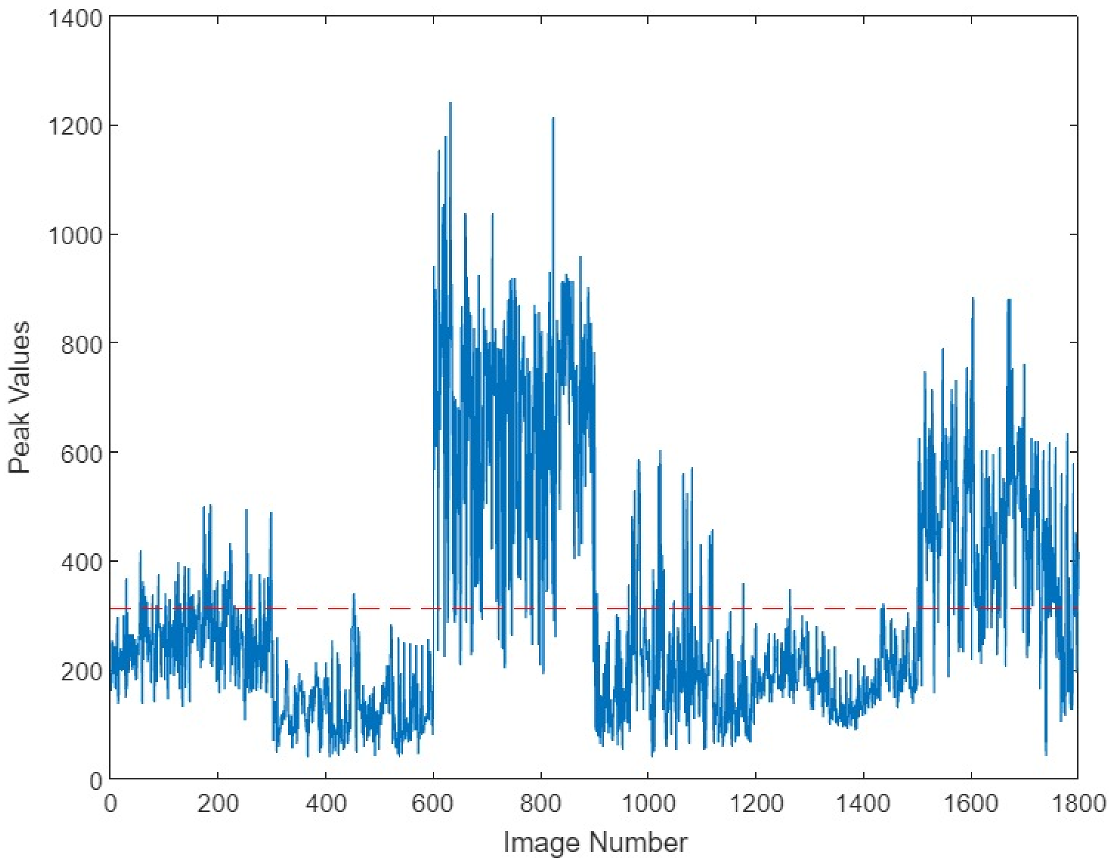


Figure 11 Threshold Value

From this graph we can observe that the peak values are in the range of 42-1241. We have taken the **threshold value as 100** for this model. It can be changed according to our convenience.

7. EXPERIMENTAL RESULTS

To validate the effectiveness of this, we have performed this method over a dataset of 1800 images. The experiment utilizes Singular Value Decomposition (SVD) to project the gray level matrix onto singular vectors and detect surface defects on steel strips. It is assumed that the surface defects occupy only a small portion of the entire image. Before detecting the defects, the color image of the strip obtained from the machine vision system is converted into a grayscale image. This conversion process yields the gray level matrix, denoted as M.

7.1 Results

7.1.1 Steel Strip with Inclusion Defect

Figures 12(b) and 12(c) provide information about the horizontal ordinate values, which correspond to the row and column numbers of the black area in the grayscale matrix, respectively. By analyzing these values, we determined the location of the defect in the image, as illustrated in Figure 12(d).

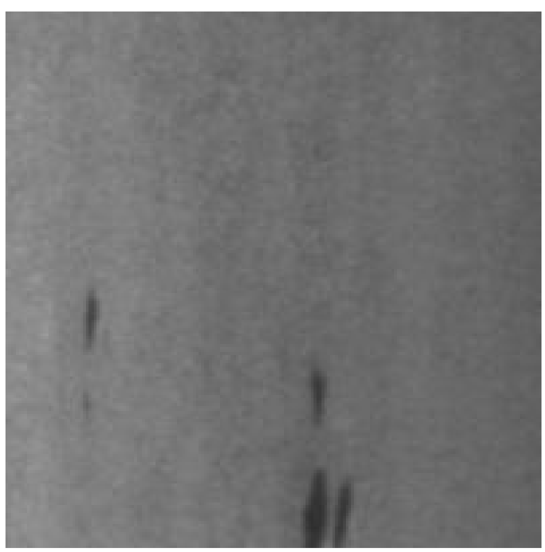


Figure 12(a) Input Image

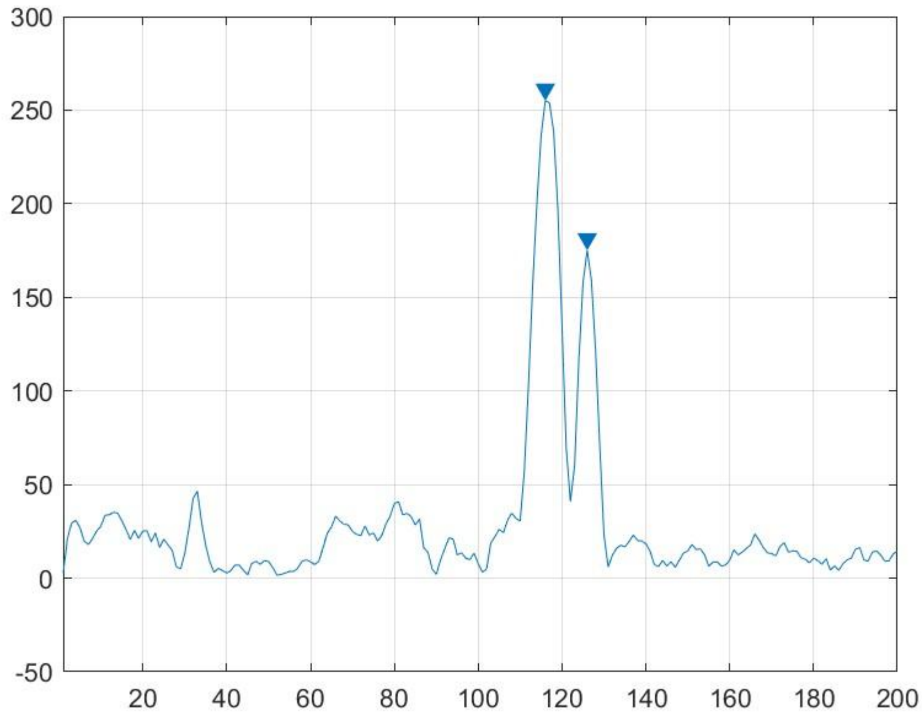


Figure 12(b) Left Projection Curve

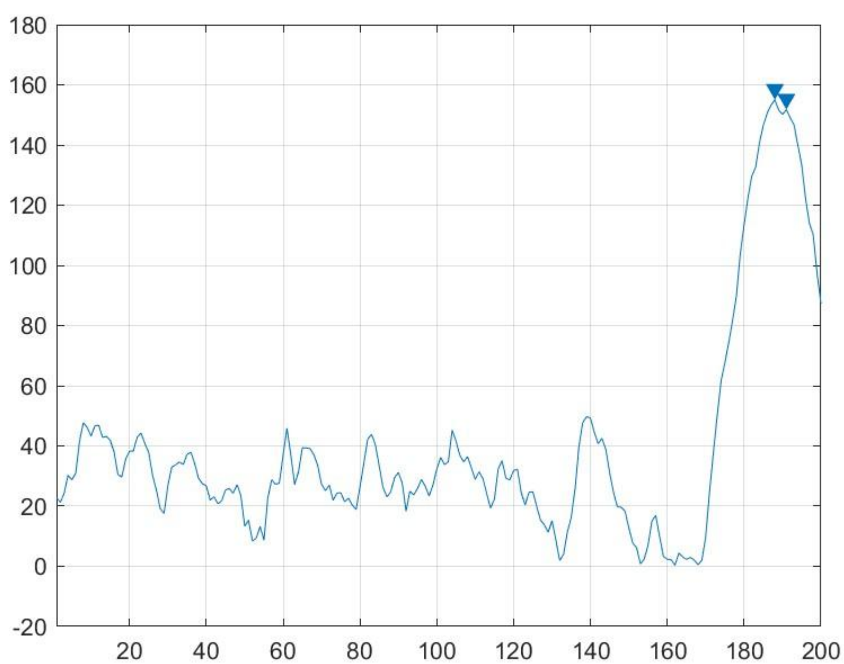


Figure 12(c) Right Projection Curve

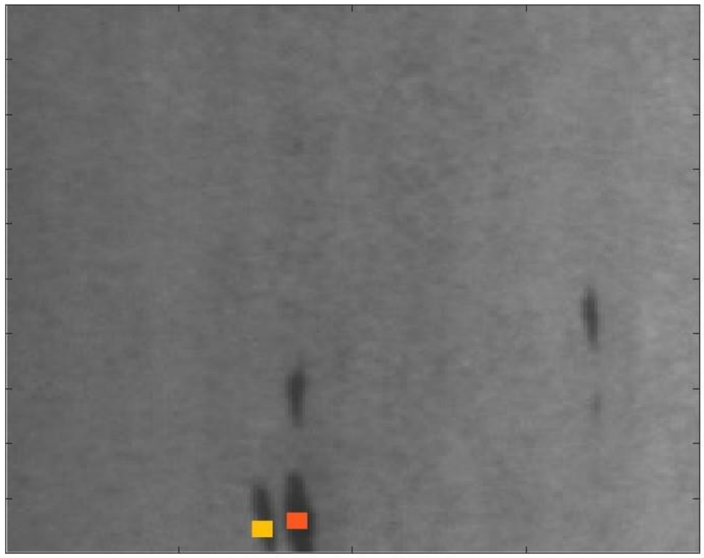


Figure 12(d) Output Image with location of defect

Figures 12: Result of steel strip with patch defect.

7.1.2 Steel strip with a crazing defect

Figure 13(a) displays a gray-level image of a steel strip with a crazing defect. This particular image is acquired using a machine vision system from a real rolling line. Based on the aforementioned steps, the first left and right singular vectors are chosen. The resulting right and left projection curves are depicted in Figures 13(b) and 13(c) respectively. Evidently, the outcomes obtained from the real image significantly differ from those in the ideal scenario. While the peaks corresponding to the defects are detected through the projection curves, the curves exhibit variations across the entire range. Furthermore, the presence of noise in the image leads to relatively large fluctuations in the curves. As a result, the determination and localization of the defect are not as straightforward as in the ideal situation. The presence of noise introduces complexity and challenges in accurately identifying and locating the defect.

To address the aforementioned limitations, further analysis is conducted by examining additional singular vectors. Interestingly, it is observed that the projections on the second left and right singular vectors exhibit similarities to those in the ideal situation. This finding suggests that by considering these additional singular vectors, it may be possible to improve the accuracy of defect detection and localization, approaching the performance achieved in the ideal scenario.

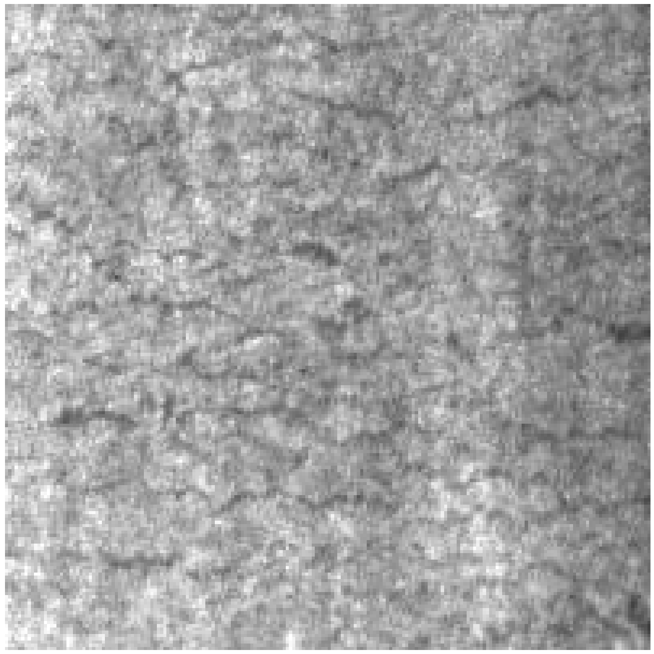


Figure 13(a) Input Image with crazing defect

\

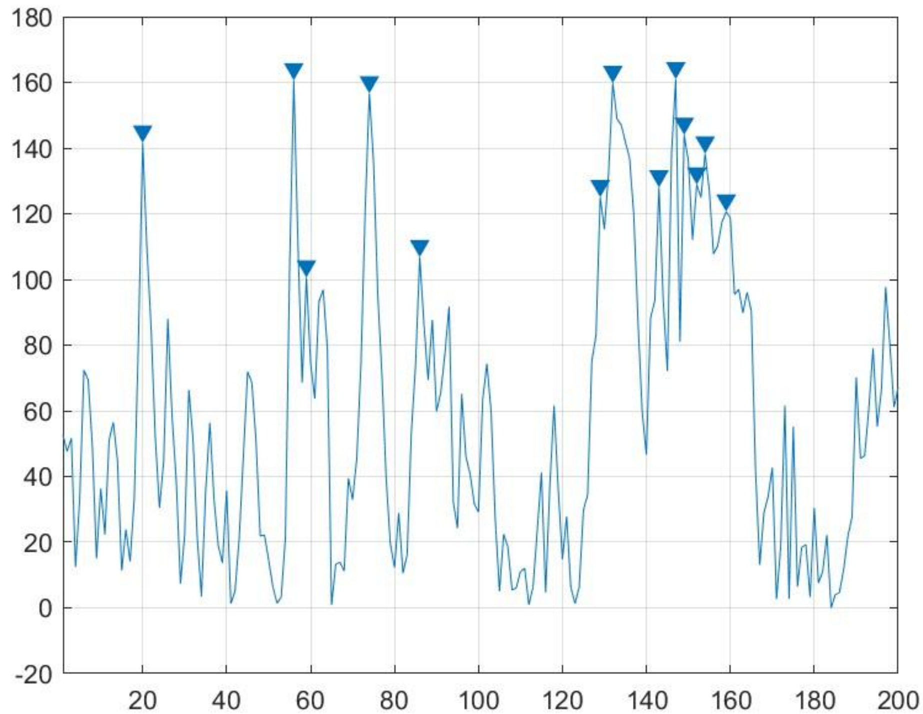


Figure 13(b) Left Projection Curve

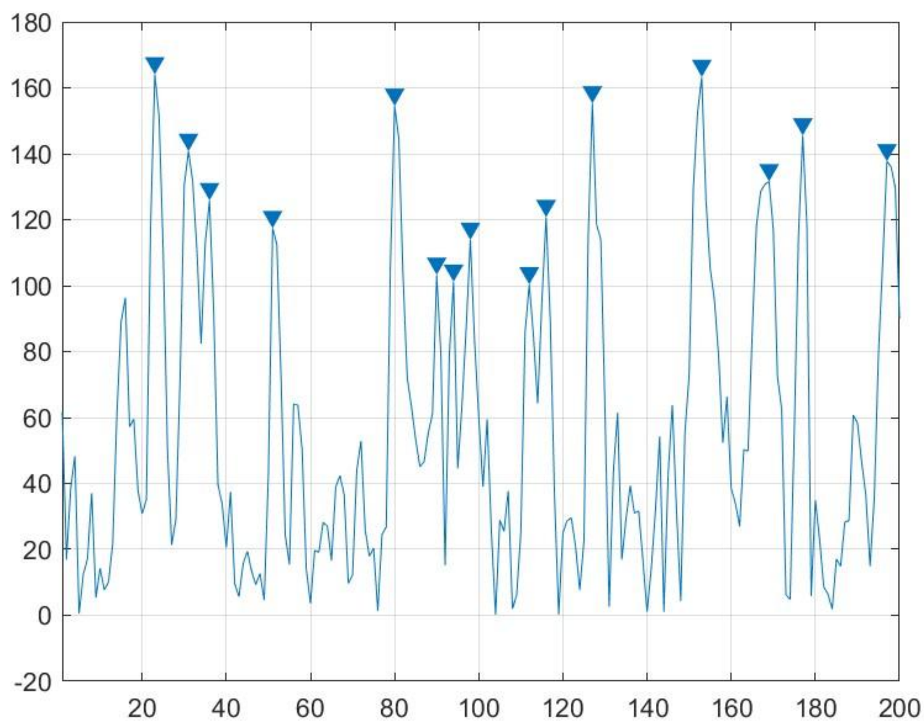
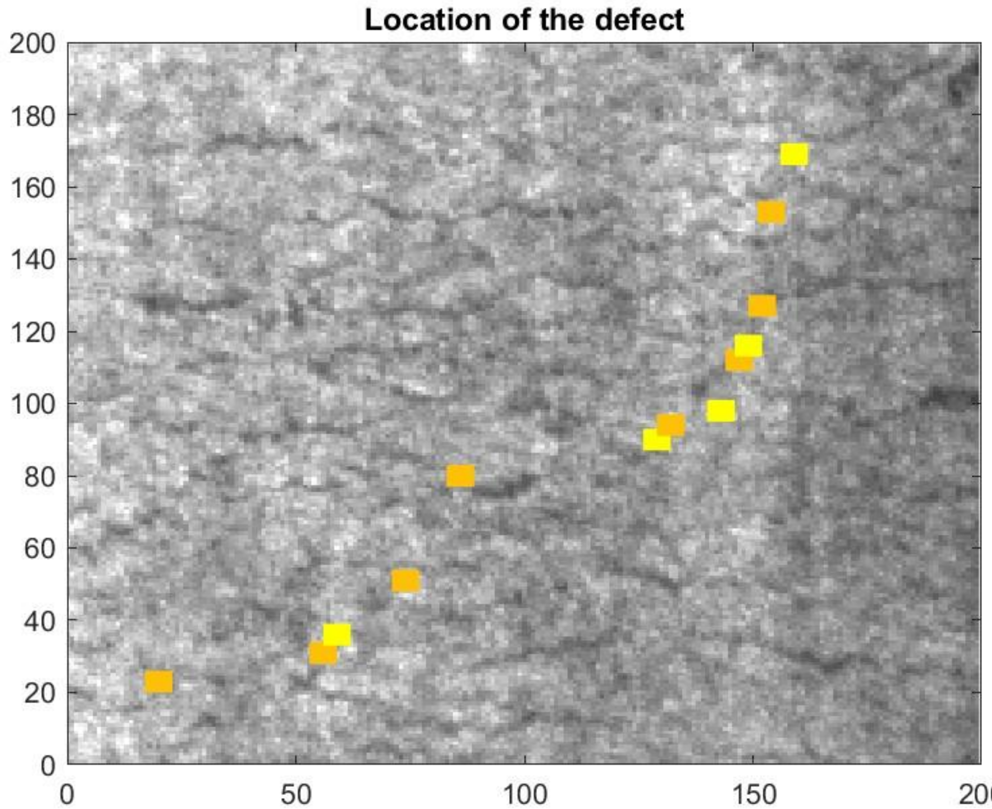


Figure 13(c) Right Projection Curve



Figures 13(d) Output Image

.

Figures 13: Result of steel strip with the crazing defect.

The significant variation in amplitudes between the normal and abnormal areas provides a clear indication for the detection and rough localization of the defect. The projection associated with the normal area appears relatively stable. This simplifies the process of detecting and locating the defect, as illustrated in Figure 13(d). By comparing the deviations, the presence and approximate location of the defects are determined.

7.1.3 Steel strip with Scratches

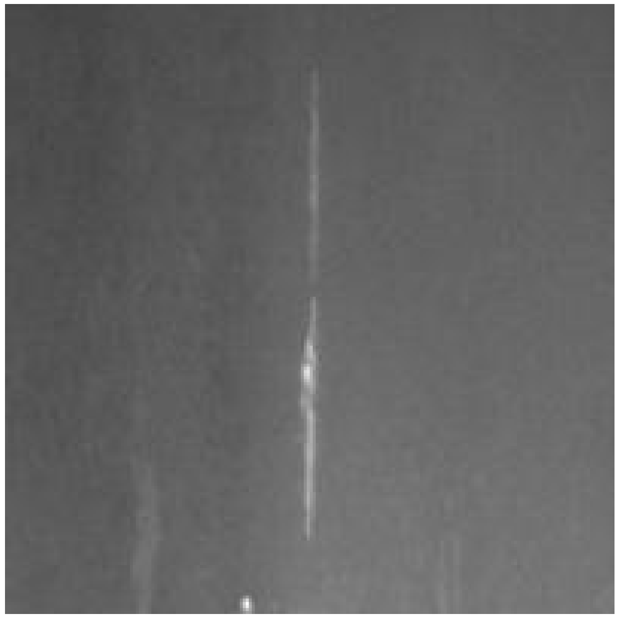


Figure 14(a) Input Image with scratch defect

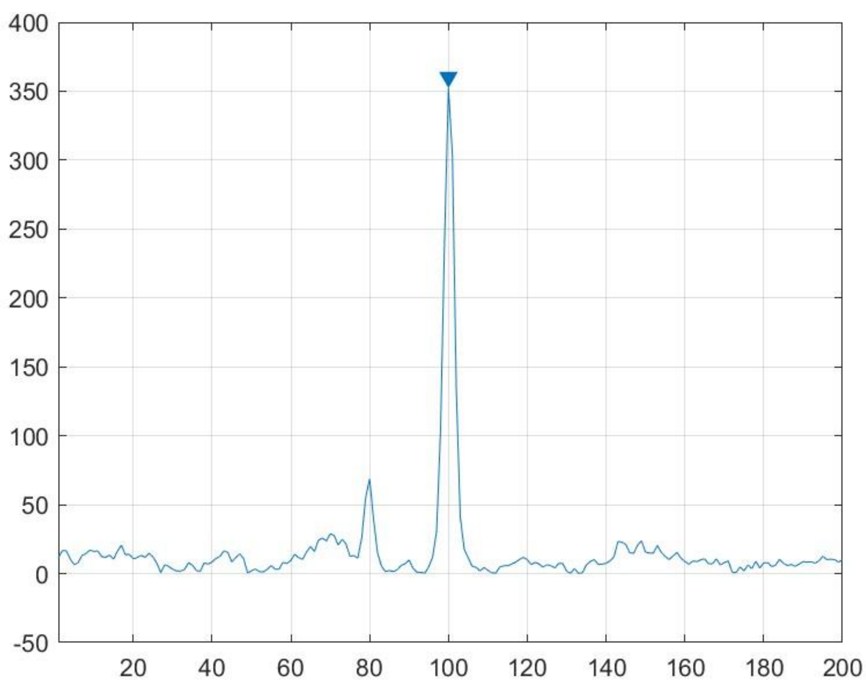


Figure 14(b) Left Projection Curve

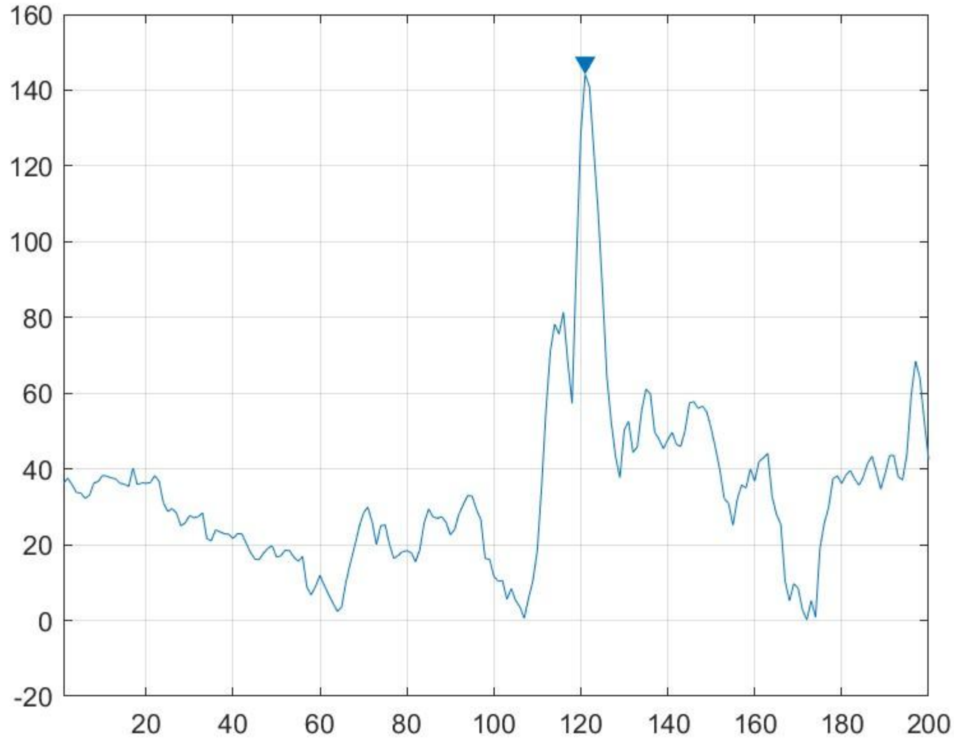


Figure 14(c) Right Projection Curve

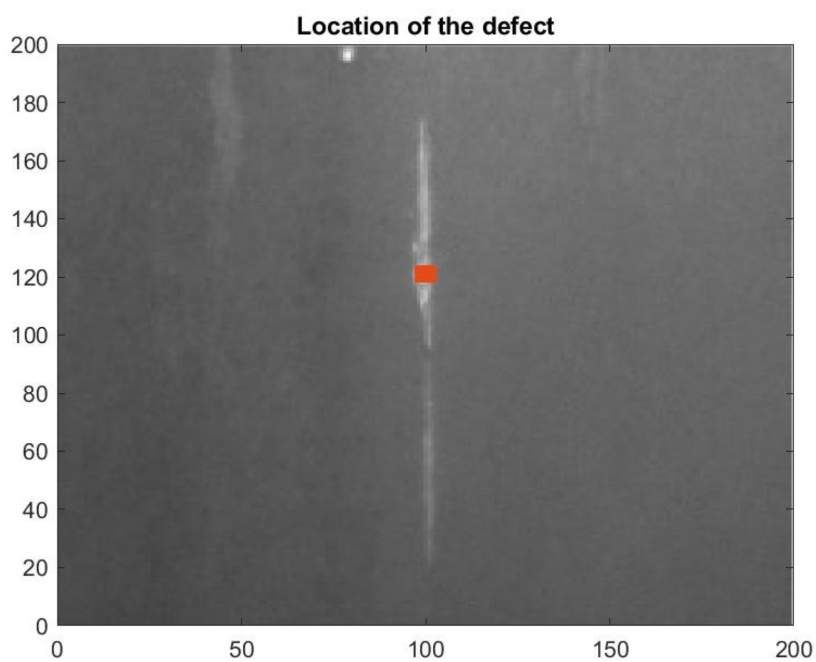


Figure 14(d) Output Image

Figures 14: Result of steel strip with the crazing defect.

7.2 Report Generation

SMART SYSTEM FOR LOCATING SURFACE DEFECTS ON STEEL STRIPS USING SVD

Defect Detection Report

Company Name: XYZ Ltd.

Date of analysis: 14-May-2023

Analysis Method: These defects are detected using Singular Value Decomposition Method (SVD).

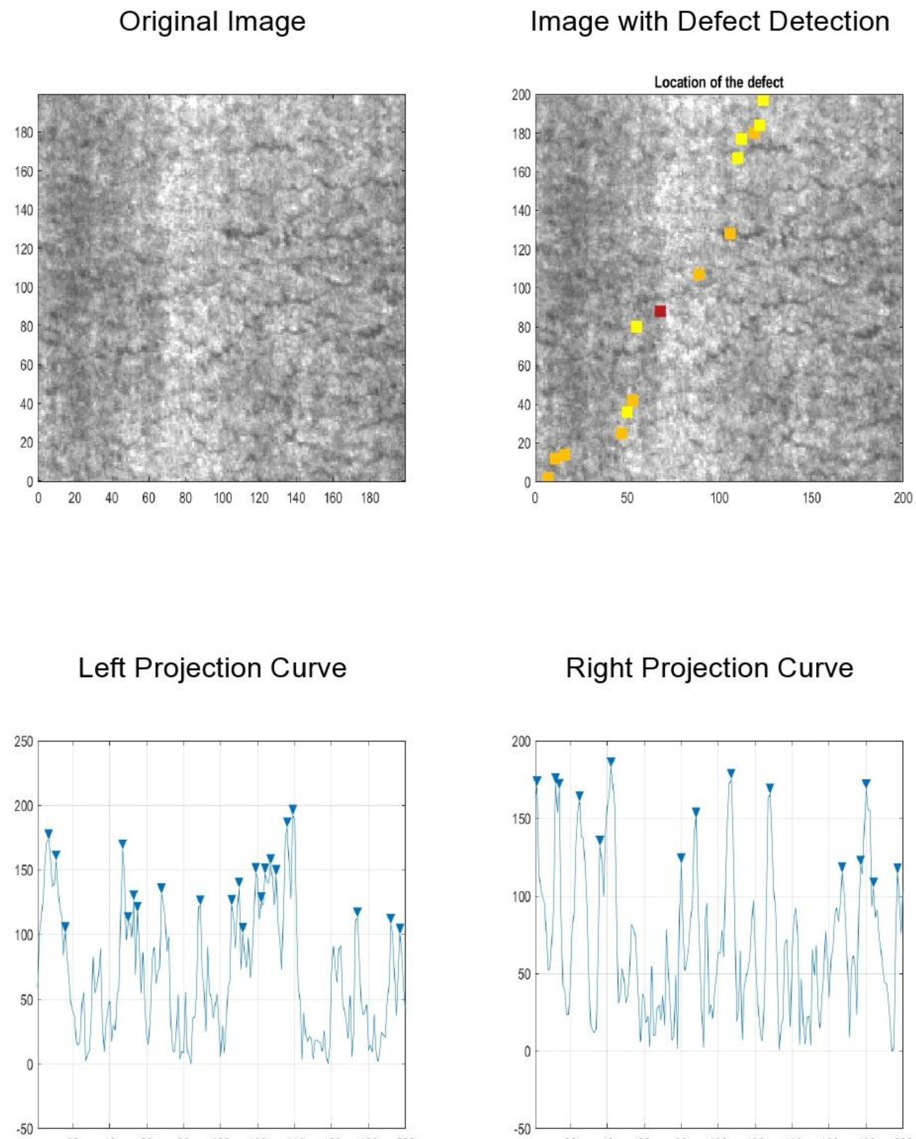
Analysis Parameters:

- Threshold Value: 100

Color	Defect Severity Range
	100-150
	151-200
	201-300
	301-400
	> 400

- Dimensions of the image used: 200 x 200 px

1


Original Image
Image with Defect Detection
Location of the defect
Left Projection Curve
Right Projection Curve

2

Defect Severity	Number of Defects	Defect Locations
	6	[[50,36],[55,80],[110,167],[112,177],[122,184],[124,197]]
	8	[[7,2],[11,12],[16,14],[47,25],[53,42],[89,107],[106,128],[119,180]]
	0	[]
	0	[]
	2	[[68,88]]

Total Number of Defects: 15

Defect Percentage: 3.3750%

Defect Detection Report

Based on the defect detection analysis conducted, we have identified and assessed 15 defects in the provided image. These defects have been visually represented in the image with detections. The analysis results and graphs provide further insights into the defect characteristics and distribution.

Disclaimer:

Please note that this report serves as a summary of the defect detection analysis. The defect detection report provided may contain mistakes or inaccuracies. Please consider the information as presented for informational purposes only. Should you have any questions or require additional information, please do not hesitate to contact us. We value your feedback and look forward to assisting you further.

3

This type of report is generated using our system. This document can be customized to add personal remarks if needed. It also includes projection curves, number of defects, defect percentage etc.

8. OUR APPLICATION

Defect detection plays a crucial role in ensuring product quality and reliability. We are excited to introduce our innovative desktop application, developed as part of our B.Tech final project. By combining the power of **Flutter** and **C#**, our application simplifies defect detection in images using the **Singular Value Decomposition** (SVD) method. With the help of advanced computational techniques, we provide accurate and efficient defect detection capabilities to users.

Here are some of the key features of our application:

- Accurate and efficient defect detection using SVD.
- User-friendly interface for easy navigation and interaction.
- Project management feature to organize and track multiple defect detection projects.
- Save and export results for further analysis and sharing.
- Installable and portable desktop application for Windows operating systems.

We believe that our application is a valuable tool for anyone who needs to detect defects in images. Whether you are a quality control engineer, a manufacturing plant manager, or a researcher, our application can help you improve the quality of your products and processes.

8.1 Installation and Compatibility:

Our application is specifically designed for Windows operating systems. To experience the capabilities of our solution, users can conveniently download and install the application using the provided installer[17]. Once installed, our application seamlessly integrates into your desktop environment, ready to assist you in detecting defects in images.

8.2 Rich Output and Report Generation:

Our desktop application goes beyond defect detection by providing rich output and report generation capabilities. After analyzing an image, users can save the results in various formats, including **images** and **PDF** documents. The generated report includes essential visualizations such as the input image, processed output image, left projection graph, right projection graph, and a detailed percentage of defect analysis. This comprehensive output enables users to analyze and share their findings effectively, supporting informed decision-making and problem-solving.

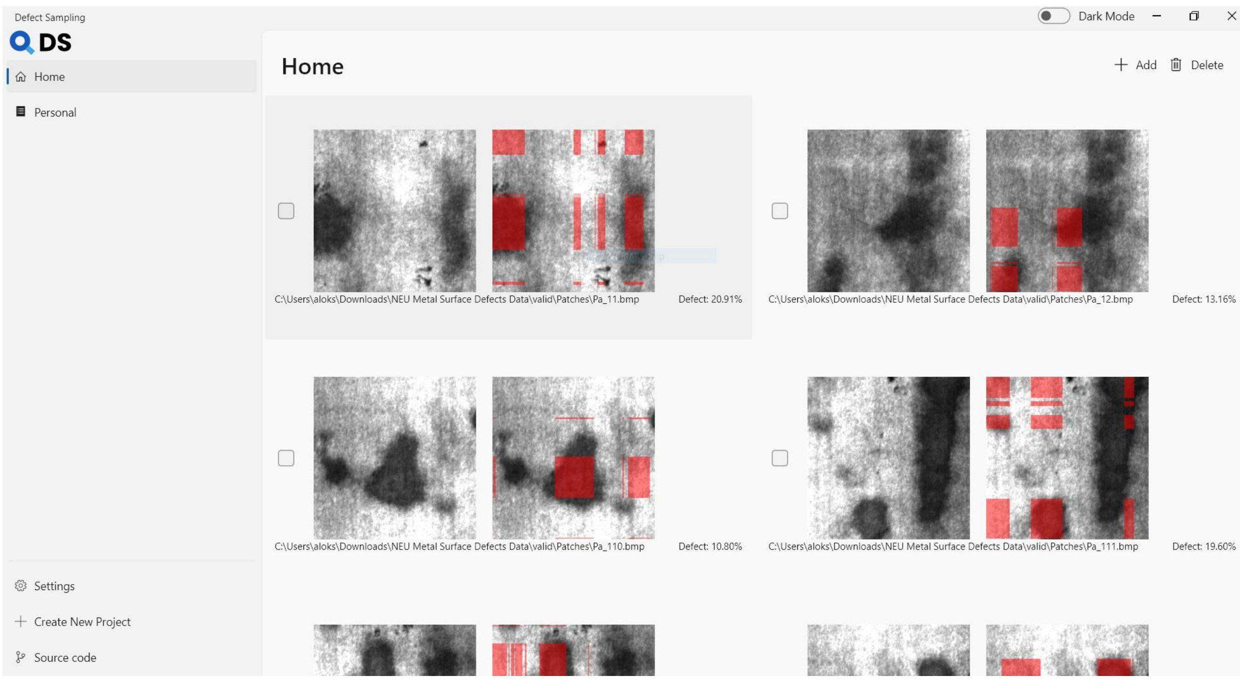


Figure 15: A screenshot of application loaded with multiple images in a project [20]

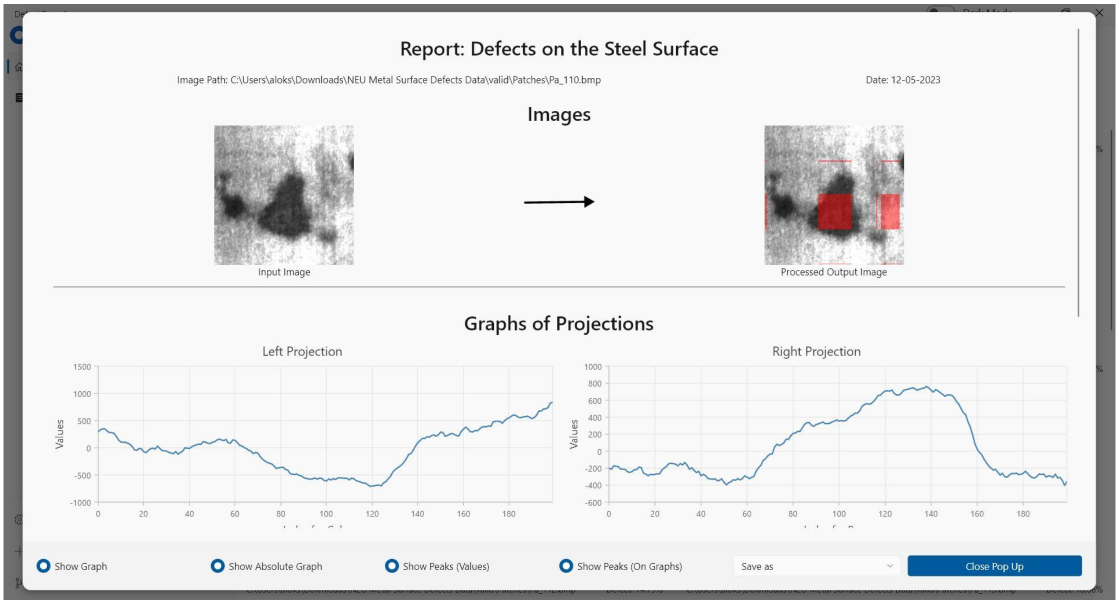


Figure 16: A screenshot of application showing generated report [20]

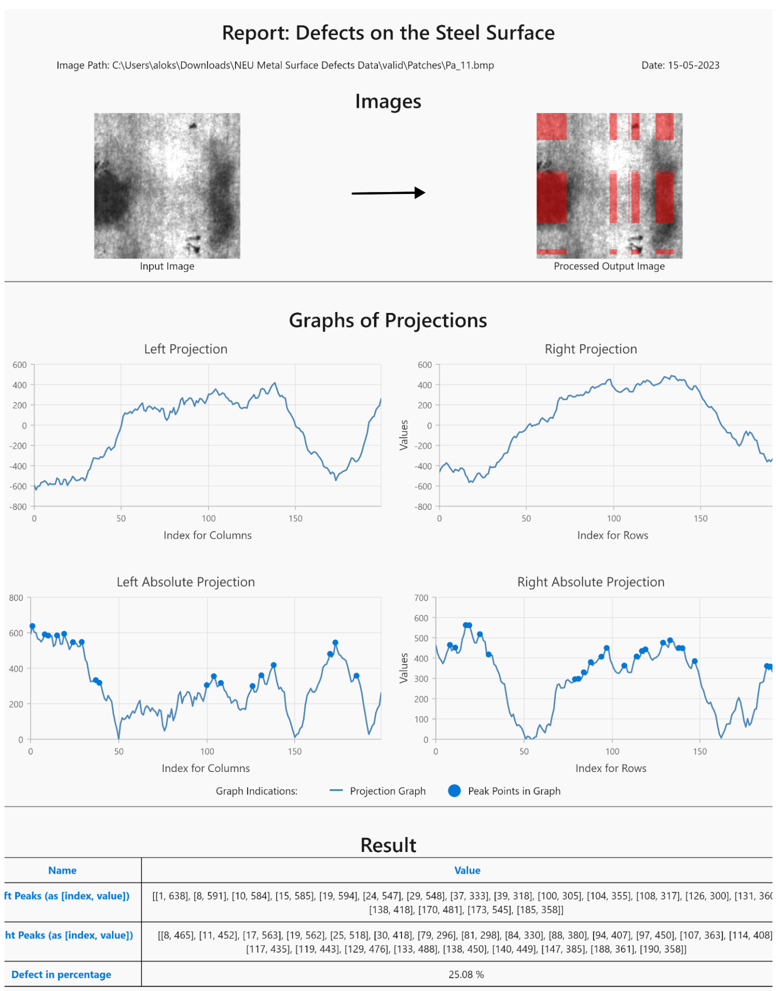


Figure 17: A sample image showing exported reported as image [20]

9. DISCUSSION

Although the results have demonstrated the effectiveness of this method, there is still a need to explore its underlying theoretical basis. In this context, there are two essential questions that should be addressed. The first question pertains to the correlation between defects and the abrupt changes observed in the projection curves. This relationship can potentially be explained by employing matrix perturbation theory. When a defect is present in an image, certain elements within its gray-level matrix undergo more significant variations compared to those in an image without any defects. However, the singular vectors of the matrix remain relatively stable. The sudden changes occur when the gray level matrix is projected onto its singular vectors. Therefore, it is proposed that the primary cause of the sudden changes in projection curves is the alteration of the gray level matrix, rather than the singular vectors themselves. Nevertheless, additional investigation is required to validate this assertion.

Another question that arises is why the projection on the second vector yields better results compared to the projection on the first vector. According to Principal Component Analysis (PCA), the principal components are ordered in a way that the first few components capture the major information of the image, while the subsequent components hold minor information. In the context of defect detection based on the previous assumption, the background of the image with defects can be considered as the major information, while the defect itself represents the minor information. More specifically, the second principal component contains a greater amount of information about the defects. In other words, projecting the gray level matrix onto the second principal component provides a more effective representation of the defect-related information.

It is important to acknowledge that when dealing with excessively large defects or a high number of scattered defects in images, the effectiveness of this method diminishes. In such cases, the defects themselves become the predominant information within the image, making it more challenging to differentiate them from the background. Moreover, when the illumination across the image is highly uneven, the results obtained from this method may also be unsatisfactory. For instance, if the light is focused on a single point, it can potentially trigger a false alarm as the concentrated light spot might be mistakenly identified as a defect.

It is noteworthy that this method, while being simple and practical, has some inherent limitations that affect the precision of defect localization. The simplicity of the method leads to roughness in two primary aspects.

- Firstly, the detected shape and area of the defects may not be accurately determined. This imprecision can result in deviations from the true shape and size of the defects.
- Secondly, the method tends to detect a higher number of defects than actually present in the image. This overestimation occurs due to the method's sensitivity to variations in the gray level matrix, which can sometimes lead to false positives.

Therefore, although the method is straightforward and useful, it should be recognized that its simplicity can lead to rough localization of defects, inaccurate shape/area determination, and an increased likelihood of detecting more defects than there actually are. Therefore, the more accurate the detection of the defect is required, the more advanced the algorithms may be adopted following the same concept.

10. FUTURE SCOPE

Here are some elaborative examples of how the SVD-based defect detection method can be applied in various domains:

1. **Wood Quality Inspection:** In the woodworking industry, the method can be employed to detect defects in wood surfaces, such as knots, cracks, or wood grain irregularities. By analyzing images of the wood surface, the method can identify and locate these defects, aiding in the assessment of wood quality for furniture manufacturing or construction purposes.

2. **Food Inspection:** The method can be applied to food quality control, where it can help detect defects or contaminants in food products. For instance, in fruit sorting processes, the method can identify bruised areas, mold spots, or other defects on the surface of fruits, ensuring that only high-quality produce is distributed.

3. **Manufacturing:** The method can be used in the inspection and quality control of manufactured products, such as electronic components, automotive parts, ceramics, textiles, or plastic materials.

4. **Medical Imaging:** It can be utilized in medical imaging techniques like X-rays, CT scans, or MRI scans to identify anomalies, such as tumors, lesions, or abnormalities in organs or tissues.

5. **Surface Inspection:** The method can be used for defect detection and quality assessment on various surfaces, including glass, ceramics, textiles, paper, or composite materials.

6. **Defect Detection in Automotive Body Panels:** In the production of automotive body panels, such as doors or hoods, the SVD-based method can be utilized to detect surface defects that may affect the quality and appearance of the panels.

7. **Plastic Industry:** By utilizing the SVD-based method, the plastic industry can effectively detect defects in injection molded parts. This enables manufacturers to identify and address issues early in the production process, ensuring high-quality plastic products and minimizing waste and customer dissatisfaction.

These are just a few examples, but the SVD-based defect detection method can be adapted and applied to various industries and domains where the identification and localization of defects are crucial.

11. CONCLUSION

In this report, we presented **a method based on Singular Value Decomposition (SVD) for locating surface defects on steel strips**. The proposed method offers a convenient and effective approach for identifying and localizing common defects found in such materials. Through a series of experiments involving various complex cases, the obtained experimental results align closely with the expected outcomes. The SVD-based method demonstrates its capability to accurately locate surface defects on steel strips, validating its suitability for practical applications.

It offers a direct approach to defect detection and localization without the requirement of image segmentation or complex modeling techniques. This simplicity makes the method highly practical and convenient for real-world applications. While the defect localization may be rough due to the straightforward locating procedures employed, if higher precision is necessary, advanced methods can be utilized while adhering to the same fundamental concept. This suggests that the initial method serves as a suitable starting point and can be enhanced further to achieve more precise defect localization when needed.

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20. Screenshots of Desktop applications