Minimizing Unplanned Downtime in Rotary Vacuum Drum Filters for Iron Ore Mining through Image-based Analysis

Sameer Prabhu[1], Amit Patwardhan[1], Naveen Venkatesh[2], Pierre Dersin[1] and Ramin Karim[1]

[1,2] *Luleå university of technology, Luleå, 97187 Sweden*
[1] *firstname.lastname@ltu.se*
[2] *naveen.venkatesh@associated.ltu.se*

ABSTRACT

A Rotary Vacuum Drum Filter (RVDF) is one of the filtering equipment used in iron mining for removing excessive moisture from slurry. One of the critical components of RVDF is a supporting wire which holds filter cloth. During filtration, due to variation in pressure the wire undergoes recursive compression and expansion which may lead to wire failure. This failure significantly impacts the integrity and efficiency of filter cloth that affects the filtration performance. If the wire failure is not detected promptly, it may lead to prolonged maintenance time, substantial maintenance cost and unplanned downtime, consequently affecting system availability. To address the issue, this work aims to demonstrate health monitoring of filtering systems in mining.

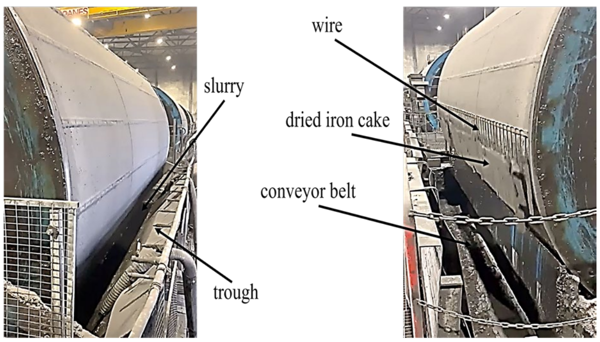
This paper introduces a vision-based monitoring approach for detecting surface defects indicative of wire-induced degradation on RVDF filter cloth. Video streams collected during operation are processed to extract the relevant surface regions for targeted analysis. The proposed methodology integrates structural feature localization and pixel-wise statistical analysis to detect deviations in surface appearance associated with wire failure. The approach enables both global health assessment and localized fault detection, to provide operators with diagnostics about the emerging failure, to take appropriate maintenance action and minimize further damage, and downtime. The focus of this work is on detection and diagnostics, and in future work a transition towards prognostics is possible by incorporating multi-modal sensor data.

1. INTRODUCTION

The processing phase in iron ore mining is generally performed to enhance the iron content in the final product through various stages that include sorting, concentrating and pelletizing. The dewatering plant in the pelleting stage plays an important role in controlling the moisture content in iron cake and to meet the process requirements for the next phase. The Rotary Vacuum Drum Filter (RVDF) (Sharad et al., 2019) plays an important role in this process by continuously separating excess moisture from the iron slurry. As shown in Figure 1, the RVDF consists of a horizontally mounted cylindrical metal drum made of a perforated plate, partially submerged in a slurry trough, with its surface covered by a filter cloth secured by supporting wire (Cieslakiewicz et al., 2024) (Sharad et al., 2019). As the drum rotates, vacuum pressure draws the slurry through the filter cloth, forming a solid iron cake with required moisture content on its surface, which is puffed or transferred on a conveyor belt for further processing.

Common failures in RVDF include rupture of filter media, degradation of filtration holes and similar challenges (Cieslakiewicz et al., 2024). Among the various components of RVDF as shown in Figure 1b, this work focuses on the filter cloth and supporting wire which are susceptible to frequent failure. The failure of the wire can be attributed to the strain caused by the cyclic pressure and vacuum cycle, in addition to the varying load effect caused by the moisture in the slurry, which directly impacts the effectiveness of filter cloth. As the wire degrades, the cloth around the impacted region might not adhere the slurry adequately, resulting in patchy regions of non-uniform filter surface. Figure 2a shows the surface during normal operation and Figure 2b shows a sample of a synthetically generated failure image. The cloth failure reduces the availability of the filter, and the resulting unplanned downtime leads to production losses. Additionally, if the operation continues after failure, the wire might get entangled around the edges of filter. This complicates the maintenance process and can significantly increase both the maintenance time and cost. A serious operational concern is the possibility of broken

a) rotating vacuum drum filter surface

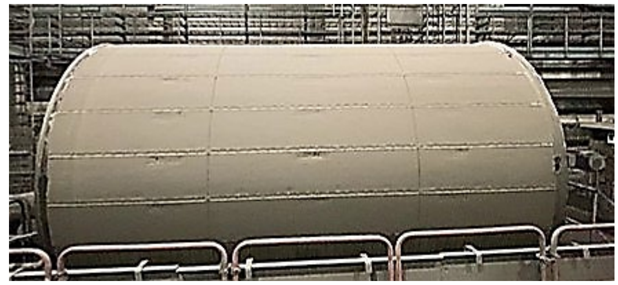


b) components of drum filter

Figure 1. Outer surface and sample components of RVDF.

fragments of wire might get trapped in downstream equipment, such as conveyor belts, potentially causing which could lead to a complete plant shutdown and result in a significant financial loss.

Despite the importance of filtration system integrity, current maintenance practices rely on manual inspection and preventive maintenance. Operators and maintenance engineers perform regular checks, including monitoring pressure values, agitation speed, and moisture content in the dried iron cake. However, these inspection measures often fail to detect early signs of degradation, and by the time failure is detected, significant damage has already occurred. A significant contributor to such operational and financial expenditure is the lack of an ineffective maintenance strategy capable of anticipating failures (Biggio & Kastanis, 2020). Predictive maintenance (PdM) offers a promising solution by utilizing historical data and analytics to predict machine failure. Prognostics and Health Management (PHM) is fundamental to PdM, which includes monitoring the evolution of the condition of a system to predict its failure (Zio, 2022). Beyond failure prediction, PHM also adds another layer that integrates maintenance strategies to increase operational efficiency and reduce unplanned downtime (Fink et al., 2020). With the advancement of sensor technology and analytics tools, PdM is the way forward (Lee et al., 2006). The three tasks of PHM defined in (Zio, 2022) are fault detection, fault diagnosis and fault prognostics. Fault



a) normal filter operation image

b) synthetically generated failure image

Figure 2. Filter image during normal operation and failure.

detection and diagnosis are essential for efficient operation of assets (Ifeanyi & Coble, 2024). PHM involves continuous asset monitoring to detect any deviations and pinpoint potential root cause and prediction of the remaining useful life (Fink et al., 2020)(Zio, 2022). In line with the PHM objectives, this work proposes an approach to detect early signs of filter cloth degradation. Figure 3 shows the pipeline of this work. Video frames are extracted to capture the filter surface, followed by isolating the region of interest containing the filter cloth. Surface analysis is then performed using intensity and texture variations to detect irregularities. Finally, section-wise localization identifies the origin of wire failure. Overall, the contributions of this paper are bi-fold:

1. An image-based approach for early detection of wire failure in RVDF, aimed at identifying surface anomalies that compromise the filter cloth integrity during operation.
2. A localization technique to precisely identify the region of wire failure, providing insights on the specific area of the filter cloth affected by degradation.

The objective of this work is to enable timely detection of failure and targeted maintenance planning, to support the development of predictive maintenance strategies.

The rest of the paper is organized as follows. Section 2 gives the related work and identifies the research gap. Section 3 presents the methodology used for the proposed approaches with results in section 4. Section 5 provides a detailed discussion, followed by a conclusion and future work in section 6.

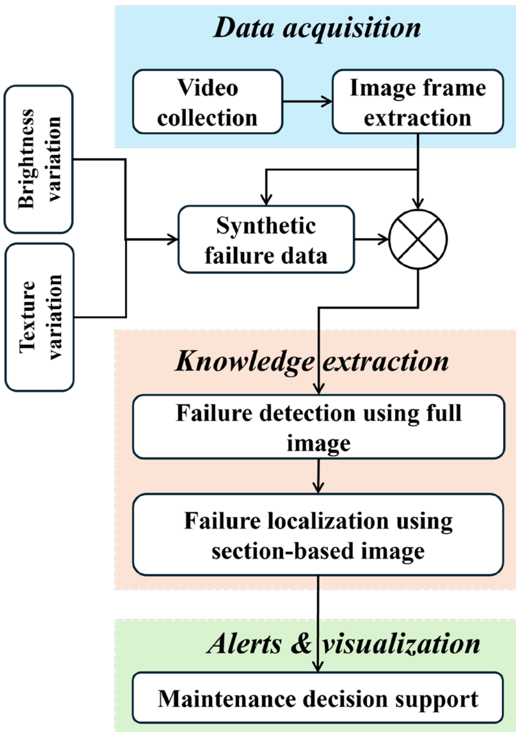


Figure 3. Flowchart of image-based failure detection and localization for RVDF.

2. RELATED WORK

Effective maintenance of industrial assets is critical to reduce downtime and optimize operational efficiency, especially in high-stakes industries such as mining. It is therefore important to prioritize the optimization of maintenance strategies (Huang et al., 2024). PHM has emerged as a reliable framework for predictive maintenance by enabling continuous system monitoring, fault detection, diagnostics, and estimation of remaining useful life (Zio, 2022) (Fink et al., 2020). PHM techniques are widely applied across industries to enhance reliability, reduce maintenance costs, and improve system availability (Huang et al., 2024) (Shin et al., 2018).

Within the broader context, vision-based approaches have increasingly been explored. A conveyor belt deviation detection approach for coal mines was presented in (Wu et al., 2023a). To extract the edges of the belt, Canny edge detection and Hough transform were applied on the processed low light images. To detect and predict soil erosion and filtration process, (Huisman et al., 2024) uses Optical Coherence Tomography (OCT) and multi-scale Convolutional Neural Network (CNN). To identify filtrate turbidity and flow states in press filter, (Cui et al., 2022) used YOLO-V5-based object detection with multi-label head. A vision-based fault diagnosis data driven approach was proposed in (Liu Binand Peng, 2022) for rolling bearings. Displacement information was extracted from vibration images to classify fault types. These studies highlight image-based analysis to capture signatures that are difficult to measure with conventional sensors.

Despite the advancement in sensor technology, commonly used data for PHM predominantly focuses on utilizing time-series sensor data, including vibration, temperature, force readings, maintenance logs (Jia et al., 2018). However, applications of vision-based monitoring in harsh industrial environments, particularly in mining equipment, remain limited. This gives a potential opportunity for exploring image-based detection and diagnostics.

Within PHM, early fault detection and localization are essential for enabling timely interventions and preventing failure escalation (Lee et al., 2014) (Jardine et al., 2006). Particularly in the context of RVDF, failure of supporting wires is a significant yet underexplored challenge. Many studies use images or optical diagnostics for system monitoring but not specifically on mechanical surface damage. To the best of our knowledge, no prior work has addressed the problem of wire failure detection and localization on RVDFs using image-based techniques. While PHM principles are well established, their application to RVDF health monitoring, particularly through machine vision, remains an open research area. This paper addresses this gap by proposing a vision-based condition monitoring approach for early detection and localization of wire-induced degradation on RVDF filter cloth.

3. METHODOLOGY

This section presents the proposed methodology for detecting wire-induced degradation on the RVDF filter cloth using image-based analysis. As discussed in section 1, when the supporting wire degrades, the filter cloth no longer adheres the filter cake uniformly. This might lead to two distinct types of visual signatures, surface non-uniformity and surface irregularity. Two complementary image analysis approaches — brightness variation and texture variation — are implemented to enable effective failure detection. The methodology consists of three main phases: (i) data acquisition and pre-processing, (ii) full image-based failure detection, and (iii) section-wise failure localization. Each phase is described in detail below.

3.1. Data acquisition and pre-processing

Video recordings of the RVDF during normal operation are collected using high resolution camera (12MP, 4K video with 60 fps). The camera is mounted approximately 3 meters in front of RVDF to ensure full coverage of the filter surface. Since installation of fixed cameras on the plant requires permission, the recordings are collected using a temporary mounted camera under supervision of maintenance engineer.

Image frames are extracted from these recordings to capture the condition of the filter surface. To validate failure detection methods, synthetic failure data is generated from the normal image frames. Due to preventive maintenance the actual failure data collection is not feasible, the design of synthetic failures is obtained through discussions with the plant maintenance engineers. To be representative of realistic failures, the wire induced filter cloth generated failures are later reviewed by the maintenance engineers. Surface irregularities on the filter cloth may not always produce significant brightness changes but often alter the texture of the cloth, both intensity-based and texture-based approaches are considered. Figure 4 shows an image of the RVDF during normal operation, while Figure 5 presents an example of the synthetically generated failure data. To standardize the input data, all image frames are resized to 512×512 pixels. The camera position remains fixed during the data collection process, which allows for consistent isolation of the region of interest (ROI). The ROI is cropped between 0.35-0.80 of image height and 0.12-0.85 of image width, corresponding to the filter cloth region, as shown in Figure 6. The video recordings are performed under typical mining plant operating conditions, including dust, vibrations from the equipment, fluctuations in illumination. This is to ensure that the acquired data represents the challenges of actual mining environments.

3.2. Failure detection using full image analysis

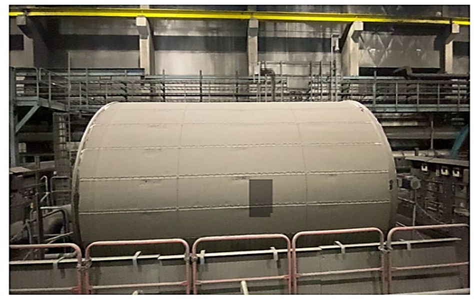
In this phase, the filter surface is analyzed using image frames from both normal operation and synthetically generated failure image data. A sliding window-based intensity variation analysis is performed on the extracted region of interest from the video data. The region is vertically divided using a sliding window approach with a window width and step size of 20 pixels. This ensures complete coverage of the filter cloth surface along the horizontal axis, as illustrated in Figure 7. For each window, the image is transformed into HSV color space, and the V-channel, which is sensitive to surface reflectance (Akbari et al., 2018), is isolated.

Let I(x, y) denote the intensity of the pixel at position (x, y) in the V-channel of the HSV-transformed image. For each sliding window W_i, the mean intensity is computed as:

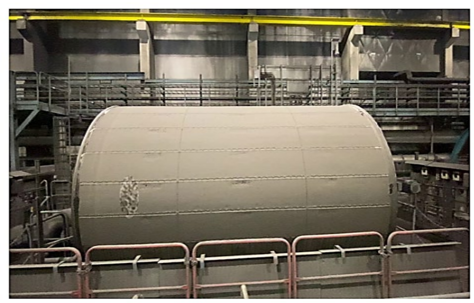
$$\mu_i = \frac{1}{|W_i|} \sum_{(x,y)\in W_i} I(x,y)$$

The intensity variation between adjacent windows is then calculated as: $\Delta I_i = |\mu_i - \mu_{i+1}|$

Figure 4. RVDF during normal operation.



a) brightness variation



b) texture variation

Figure 5. RVDF during synthetically generated failure.

Figure 6. RVDF region of interest.

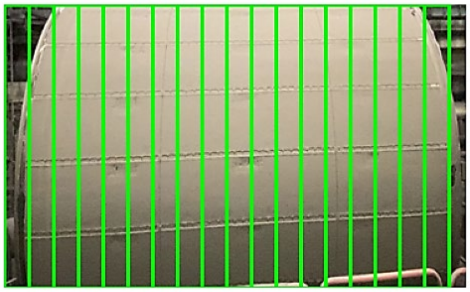


Figure 7. Sliding window covering the filter surface.

Regions with significantly higher ΔI_i values indicate potential surface defects associated with wire failure.

For corner windows, a single-side intensity comparison is applied. These intensity variation values are plotted to generate an intensity profile representing the condition of the filter surface.

To capture texture variations, the Sobel operator (Xu et al., 2021) with a kernel size of 3 is applied in the horizontal direction. This computes the first-order image gradient, which reflects edge and texture information across the filter surface. The Sobel operator is applied in the horizontal direction to compute the first-order gradient:

$$G_x(x,y) = \frac{\partial I(x,y)}{\partial x}$$

The mean absolute gradient magnitude within each sliding window W_i is given by: $G_i = \frac{1}{|W_i|} \sum_{(x,y)\in W_i} |G_x(x,y)|$

A noticeable increase in G_i may indicate texture irregularities, which can signal early-stage degradation of the filter cloth surface.

3.3. Failure localization using section-based analysis

Following the full image analysis, this phase focuses on localizing the failure initiation point by analysing individual sections of the RVDF. The surface of RVDF considered for this work is divided into 24 uniformly sized sections. To extract these sections, edge detection is first performed on the filter cloth image using the Canny algorithm with intensity threshold set at 50 and 150 ensuring a good balance between noise suppression and edge retention. Next, the Hough Line Transform is applied to detect prominent horizontal lines on the filter surface (Wu et al., 2023b). Lines that meet the length threshold set at 100 pixel and have an orientation close to horizontal are retained. The extreme coordinates of these lines are identified using their corner points, as shown in Figure 8. A rectangular section of the filter surface is then defined by connecting these extreme points, illustrated in Figure 9. The width of this section is measured, and since all 24 sections have equal dimensions, additional sections are extracted by vertically shifting the first identified section by the computed width. To account for the curvature of the RVDF surface, pixel adjustments are applied during this shifting process. Figure 10 shows the multiple sections identified on the RVDF. The two image analysis approaches described in Section 3.2, brightness variation and texture variation are applied to both single and multiple sections. This enables precise localization of the failure initiation point by detecting irregularities on the filter cloth surface.

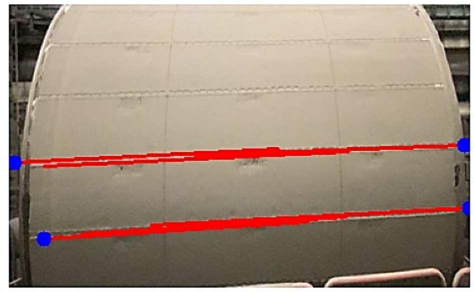


Figure 8. Detected horizontal lines (in red) and extreme points (in blue).

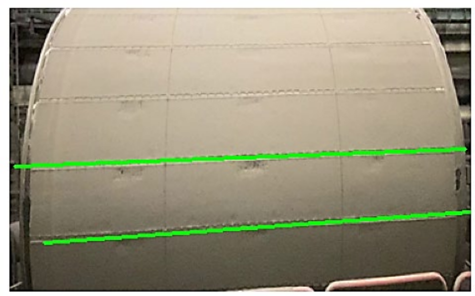


Figure 9. RVDF single section identification.

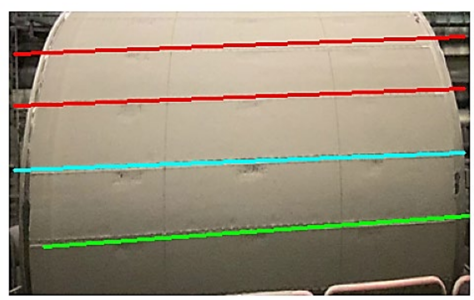


Figure 10. RVDF multiple section identification.

The choice of using methods like intensity variation and gradient analysis provides a direct and interpretable connection to the wire induced degradation of filter cloth. The advanced data-driven methods which require extensive training datasets, the proposed approaches are effective with limited data.

4. RESULTS AND ANALYSIS

This section presents the results obtained from the vision-based detection system applied to RVDF images. The analysis is performed incrementally, starting with global failure detection across the full filter surface, followed by localized detection through section-wise analysis. Texture-based detection is also evaluated to capture subtle surface irregularities.

4.1. Detection of failure on full image

In this phase, failure detection is performed on the entire RVDF surface, considering it as a single image. A horizontal sliding window divides the image vertically into equal-width sections as shown in Figure 11.

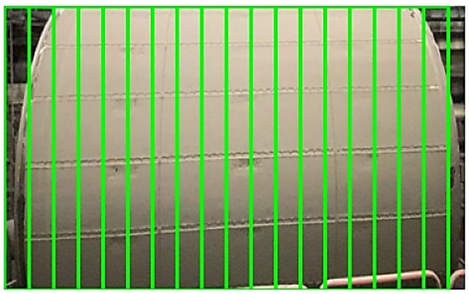


Figure 11. Sliding window for normal filter operation.

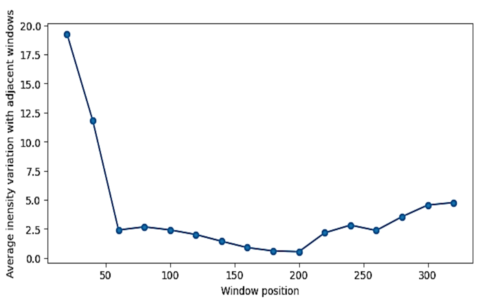


Figure 12. Intensity variation between adjacent windows under normal operation for Figure 11.

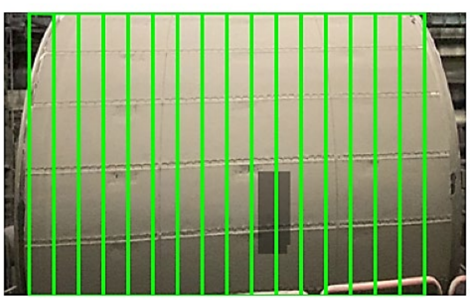


Figure 13. Sliding window for failure data.

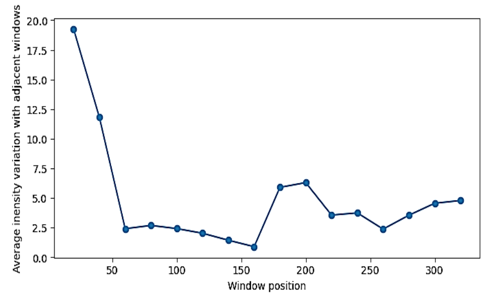


Figure 14. Intensity variation between adjacent windows during failure for Figure 13.

For each window, the mean intensity variation relative to adjacent windows is computed. This intensity profile represents the filter surface condition.

Normal operation: Under this condition, the intensity variation profile remains consistently low across the entire surface, except near the drum filter edges as shown in Figure 12. The intensity variation for central windows remains below 5, indicating a uniform and healthy surface. This analysis serves as a baseline of a healthy drum filter, giving assessment over the entire drum filter image.

Failure detection: The ability to detect failures is evaluated using an artificial defect, which resembles cloth deformation due to wire failure. Figure 13 shows sliding window analysis on failure image. In the presence of failure, a distinct spike as shown in Figure 14 appears in the intensity variation profile, indicating the affected window. This confirms the system's ability to detect failures across the full image. However, this approach does not localize the failure precisely.

4.2. Detection and localization of failure

To improve localization, individual sections of the drum filter surface are extracted using the Hough Transform as discussed in section 3.3. Figure 9 shows the detected section with green horizontal lines. Sliding window analysis is performed on this extracted section. Variation in pixel intensity is computed to detect localized failure.

Normal operation: Except for the edges of filter, intensity variation is consistently low for normal filter surface as shown in Figure 15.

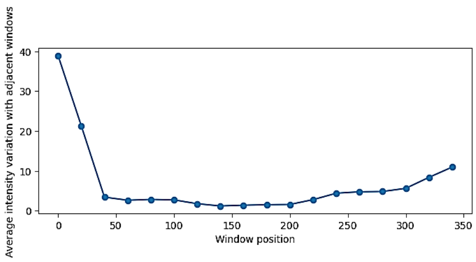


Figure 15. Intensity variation per section between adjacent windows during normal operation for Figure 9.

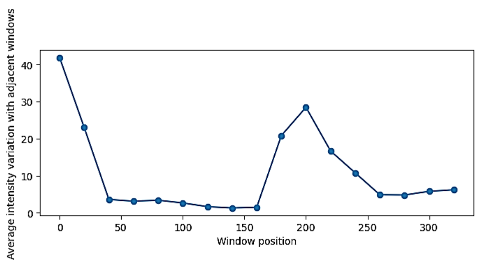


Figure 16. Intensity variation per section between adjacent windows on a failure data corresponding to Figure 9.

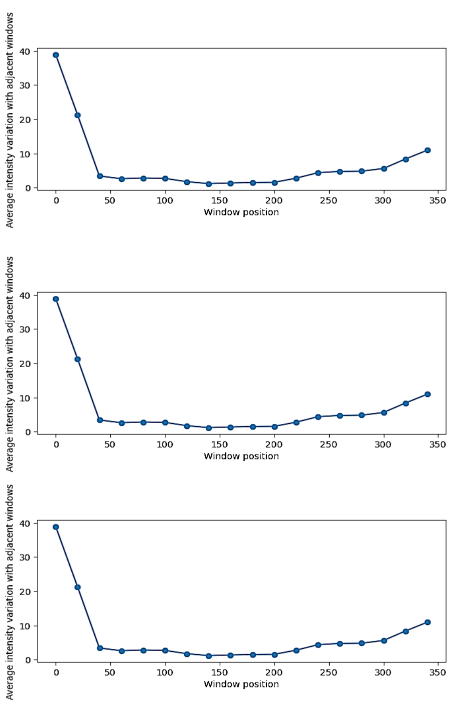


Figure 17. Intensity variation between adjacent windows for all the three sections during normal filter operation for Figure 10.

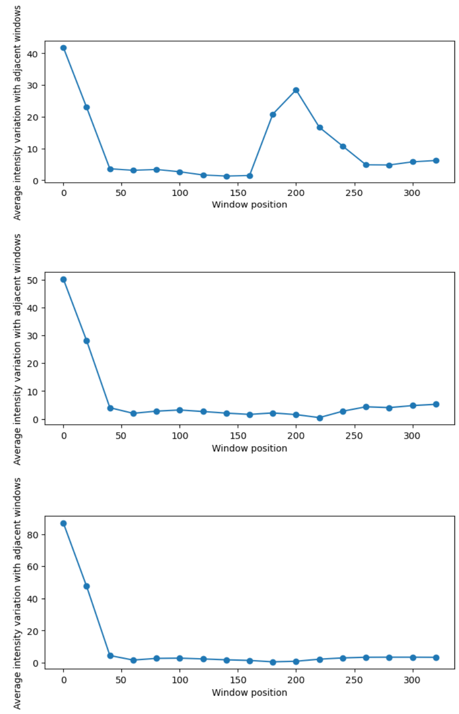


Figure 18. Intensity variation between adjacent windows for all the three sections during failure data corresponding to Figure 10.

Failure detection: In the presence of cloth failure within the same section of filter a distinct peak is observed in the intensity variation profile as shown in Figure 16.

The rotation speed of drum filter is constant, and once the horizontal section is identified, further sections can be captured as they enter the region of interest sequentially. Analyzing all the 24 sections individually requires capturing data for 24 positions which increases data acquisition time. To optimize processing, multiple sections are extracted from single image frames.

Multiple section analysis: Using the same sliding window method, intensity variations are computed for each section of Figure 10. For normal operation, as shown in Figure 17, the intensity variation profile remains low. In the presence of failure, spikes in the profile indicate the affected sections, as shown in Figure 18. This approach reduces the data acquisition requirement to 8 images for complete RVDF surface coverage.

4.3. Detection of texture-based failure

The HSV V-channel based sliding window approach proved to be ineffective when detecting failure with texture distortion. Figure 19 shows synthetically generated surface texture irregularities that might arise during RVDF operation.

To address the limitations of section 4.1 and 4.2 and to detect failure reflected by texture distortion, a gradient-based approach is implemented as discussed in section 3.2. The individual drum filter section is identified using Hough transform, and Sobel filter is used to compute horizontal gradients. Figure 20 shows the mean gradient magnitude profile across the windows. The rise in magnitude is observed in the region corresponding to filter cloth failure reflected in texture distortion, except the corners. The proposed approaches allow early failure detection, which ranges from texture change to complete detachment of filter cloth.

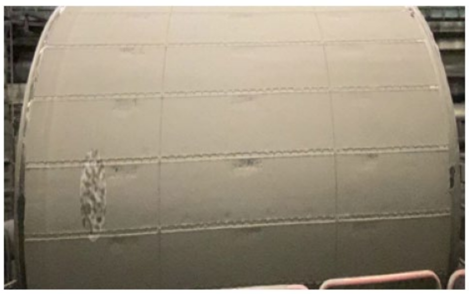


Figure 19. Synthetically generated cloth failure resembling texture irregularities.

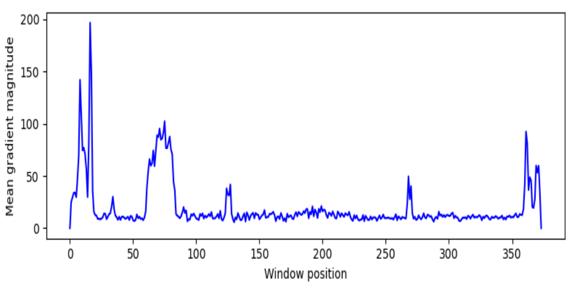


Figure 20. Gradient magnitude profile across windows for a section of filter for Figure 19.

5. DISCUSSION

This work demonstrates that image-based monitoring is a viable solution for early detecting of wire failure in RVDF. The intensity variation analysis in the HSV-V channel color space reliably identifies regions where the slurry fails to adhere to the filter cloth, indicating major surface defects. Under normal operating conditions, the intensity variation across the filter surface remained low, while failure patterns produced a distinct, localized spike in the variation profile. This confirms the method's ability to distinguish between healthy and degraded regions. In addition, the gradient-based texture analysis captured distortions in the cloth surface, which are not always visible through intensity variation alone. The section-wise localization method further improves the detection process by isolating the specific area of the wire failure initiation. Another important outcome is the reduced number of images required for complete drum coverage from 24 to 8 through multiple-section analysis, enhancing practicality for real-time use.

This work relies on synthetically generated failure data which allowed validation of the proposed method; however, real-world data is essential to verify the performance. Also, the current method relies only on visual data, which is sensitive to illumination, camera placement, dust, factors that are common in mining environment. For more comprehensive health assessment, additional process parameters such as pressure, slurry density and flow rates need to be integrated.

6. CONCLUSION AND FUTURE WORK

This work presented a vision-based monitoring framework for early detection and localization of wire failure in RVDF. The proposed method effectively identifies both significant and minor surface irregularities caused by wire degradation. The section-wise localization enhances diagnostic accuracy, assisting maintenance engineers to identify the failure initiation and providing insights to support timely and targeted maintenance interventions. The demonstrated reduction in data acquisition requirements through multi-section analysis improves the feasibility of this method for real-time implementation. By enabling early detection of wire failure, the proposed approach has the potential to reduce unplanned downtime, increase system availability, and maintain product quality, thereby contributing to overall health management.

This paper primarily focuses on failure detection and diagnosis tasks of PHM. The integration of multimodal sensor data such as pressure, slurry density, and quality will be required for the transition towards prognostic capabilities. This might facilitate the development of image-based diagnostics with time-series based prognostics model. Moreover, exploring the temporal evolution of image features can enable tracking the degradation pattern of RVDF from healthy to fault state. Such approaches might contribute to estimating the remaining useful life of the filter and enable a shift from reactive to predictive maintenance strategies.

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BIOGRAPHIES

Sameer Prabhu is a PhD candidate in the Division of Operation and Maintenance Engineering from Luleå University of Technology, Sweden. His research focuses on the development of tools and methodologies utilizing Artificial Intelligence with applications in the construction and mining industries. Prior to this, he has worked as a Machine Learning engineer in a Swedish consultancy firm. His background is in signal and image processing with applications in Machine Learning.

Amit Patwardhan is a senior lecturer in the Division of Operations and Maintenance Engineering at Luleå University of Technology, Sweden. His research focuses on asset health management, spatial data processing, and digital twins.

Naveen Venkatesh is a Postdoctoral Researcher in the Division of Operations and Maintenance Engineering at Luleå University of Technology, Sweden. His research focuses on fault diagnosis, condition monitoring and renewable energy systems. He has published over 60 research articles across various application domains.

Pierre Dersin is an adjunct professor in the Division of Operations and Maintenance Engineering at Luleå University of Technology, Sweden, and the president and the founder of technology consulting firm Eumetry sas, 78430 Louveciennes, France, after many years at Alstom as reliability master expert and, most recently, the RAM and Prognostics and Health Management (PHM) director. He has published extensively, including the book Modeling Remaining Useful Life Dynamics in Reliability Engineering (Taylor & Francis, 2023). His current research interests include systems of systems and the confluence of RAMS and

PHM. Dersin has a PhD in EE from the Massachusetts Institute of Technology, Cambridge, MA, USA. He is a Member of IEEE.

Ramin Karim is a PhD in Operation and Maintenance Engineering with specialization in eMaintenance. Currently, he is a Subject Head and Professor in the Division of Operation and Maintenance Engineering at Luleå University of Technology and Director of the Centre of Intelligent Asset Maintenance (CIAM). He has worked for more than 15 years in IT industry after obtaining his degree in computer science. He is responsible for the eMaintenance LAB, an applied laboratory for research and innovation in Industrial AI and eMaintenance. His research interest includes data analytics and predictive technology closely connected to operation and maintenance of industrial assets. He has initiated and developed the concept and platform called 'AI Factory', which is a universal concept for cross-industrial data and model sharing based on digital and AI technologies.