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MODELING BUBBLE RECOVERY PROCESSES IN A VIDEO IMAGE

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Abstract - This study investigates the gas motion through the froth of a prototype bi-dimensional flotation cell. Using advanced video and image analysis techniques, surface velocity data obtained with a Visiofroth system were validated by comparing them with manual tracking results of bubble motion on the froth surface. Images for manual tracking were captured using a high-speed video camera. Additionally, discharge velocity profiles were analyzed as a function of froth height over the launder lip under different froth Crowder angles and superficial air rates. An increasing froth discharge velocity from the lip level to the top of the froth was observed.

Air recovery was estimated using the velocity profile and compared with values derived from surface velocity estimation. Results indicated differences from 24% to 47% in air recovery when froth flow area at the lip was considered. However, both approaches displayed similar trends under varying JG and froth Crowder angles. Using top-of-froth velocity alongside the froth flow area at the Visiofroth location resulted in air recovery values closer to those obtained from the discharge velocity profile at the lip.

Keywords - *video, video stream, interlays, Visiofroth system, effects, CNNs.*

1.INTRODUCTION

Water flowrate in the concentrate stream was estimated based on operational variables and compared with measured values. A strong correlation was found when Visiofroth-measured discharge velocities and froth height over the lip were considered. Similar results were obtained when the water flowrate was estimated using discharge velocity profiles at the lip. The study further examined the effects of bubble coalescence and breakage on froth stability and their role in influencing mineral recovery efficiency.

Flotation is a critical process in mineral processing and wastewater treatment, where gas bubbles play a significant role in separating valuable minerals from unwanted materials. The froth zone in flotation cells affects both the concentrate grade and mineral recovery. Consequently,

understanding bubble behavior and air recovery dynamics is essential for optimizing flotation efficiency. Several studies have attempted to describe froth transport mechanisms using mathematical modeling, experimental techniques, and image analysis.

Recent advancements in flotation research include mathematical modeling approaches developed by Neethling and Cilliers, and studies on froth recovery by Tsatouhas et al., Seaman et al., and Yianatos et al. Additionally, investigations into entrainment mechanisms (Savassi et al., Zheng et al., Yianatos et al.) and flotation kinetics (Gorain et al., Ata et al., Honaker et al.) have provided valuable insights into froth behavior.

The application of machine vision systems in flotation, such as Visiofroth (Metso Minerals), METCAM FC (SGS), and FrothMaster™ (Outotec), has enhanced froth characterization and process optimization. In addition, new research focuses on integrating artificial intelligence (AI) and machine learning (ML) techniques to predict flotation performance in real-time. AI-based algorithms analyze froth surface characteristics such as bubble size, texture, and velocity to optimize reagent dosage and aeration rates, thereby improving overall recovery efficiency.

2.METHODOLOGY

The study employed a bi-dimensional flotation cell setup, where gas motion was recorded using high-speed video cameras and analyzed using an image processing system. Froth surface velocity measurements were obtained using the Visiofroth system, which utilizes image-based tracking of bubbles. Additionally, froth discharge velocity profiles were measured as a function of froth height over the launder lip for different Crowder angles and superficial air rates. Air recovery estimations were performed based on discharge velocity profiles and compared with surface velocity estimations.

A novel approach was also introduced by implementing deep learning-based image segmentation to classify froth texture and predict recovery efficiency. Convolutional Neural Networks (CNNs) were employed to enhance feature extraction, allowing more accurate identification of bubble clustering patterns and froth stability metrics.

Mathematical formulation for air recovery estimation:

where is the air flow rate at the froth discharge and is the initial air flow rate introduced into the system.

Algorithm for Bubble Recovery Analysis:

1. Capture High-Speed Video Footage of the Flotation Cell

- Use a high-speed camera (e.g., Phantom VEO, Photron, or similar) to record the flotation process.

- Select an appropriate frame rate (e.g., 500–2000 fps) depending on bubble dynamics.
- Ensure proper lighting to reduce shadows and glare.
- Mount the camera at an optimal angle to capture the froth surface without distortion.

2. Extract Frames and Preprocess Images Using Noise Reduction Techniques

- Convert video footage into individual frames using OpenCV (cv2.VideoCapture).
- Apply image denoising techniques:
  - **Gaussian blur** or **median filtering** to reduce random noise.
  - **Adaptive histogram equalization** (CLAHE) to enhance contrast.
  - **Morphological operations** (e.g., opening/closing) to remove small artifacts.

3. Apply Image Segmentation Using CNNs to Detect and Track Bubble Motion

- Use Convolutional Neural Networks (CNNs) to segment bubbles from the froth.
- Potential approaches:
  - **U-Net or Mask R-CNN** for pixel-wise segmentation of bubbles.
  - **YOLO or Faster R-CNN** for object detection of bubble clusters.
  - **Optical flow methods** (e.g., Farneback or DeepFlow) to track bubble motion between frames.
- Train the model using labeled datasets of flotation froth images.

4. Measure Froth Surface Velocity Using Visiofroth Data

- **Visiofroth** is an industrial tool that provides real-time froth velocity estimation.
- Methods to estimate velocity:
  - **Particle Image Velocimetry (PIV)**: Analyzes displacement of bubbles between consecutive frames.
  - **Optical Flow Algorithms**: Estimate pixel movement direction and speed.
  - **Feature Tracking**: Identify distinct bubble structures and track them over time.

5. Estimate Air Recovery by Analyzing Velocity Profiles and Froth Flow Area

- Air recovery is calculated as the fraction of air entering the froth phase that is successfully recovered.
- Key metrics:
  - **Froth velocity profile**: Helps estimate mass transfer and froth stability.

- **Bubble coalescence and bursting**: Indicate air loss.
- **Froth depth and foam texture**: Provide insights into flotation efficiency.

6. Optimize Flotation Performance by Adjusting Operational Variables Based on AI-Driven Predictions

- AI models can predict flotation performance based on froth characteristics.
- Key operational variables to optimize:
  - **Air flow rate**: Affects bubble size and stability.
  - **Reagent dosage**: Alters bubble-particle attachment efficiency.
  - **Pulp level and froth depth**: Control retention time and air recovery.
- Machine learning models (e.g., Random Forest, XGBoost, Deep Learning) can predict the best settings for maximizing flotation efficiency.

3. RESULTS AND DISCUSSION

The study demonstrated that froth discharge velocity increases with froth height. Air recovery estimations based on velocity profiles exhibited a 24%-47% difference compared to those derived from surface velocity measurements. Despite these differences, both methods showed similar trends under varying operational conditions. An increase in air recovery was observed with increasing froth Crowder angle and JG value. Additionally, a higher concentrate water flowrate correlated with higher air recovery, suggesting a potential decrease in concentrate grade due to fine particle entrainment.

A comparative analysis of flotation equipment designs and their impact on metallurgical performance revealed that proper control of air flowrate and froth depth significantly enhances mineral recovery and concentrate grade. Advanced control strategies based on froth discharge velocity, such as those proposed by Barría and Valdebenito, can optimize flotation performance.

Further analysis using AI-driven models indicated that integrating image analysis with predictive analytics could significantly improve flotation efficiency by reducing variability and optimizing reagent use. This finding suggests that future flotation cells should incorporate automated monitoring systems equipped with AI-enhanced vision devices for improved decision-making and process control.

Mathematical relation for bubble velocity estimation:

where is the displacement of the bubble in the froth layer, and is the time interval.

4. CONCLUSION

This study highlights the significance of using high-speed video analysis and machine vision systems in flotation research. The results confirm that froth

behavior can be effectively analyzed using image-based surface velocity estimations, providing valuable insights for process optimization. The integration of AI and ML techniques presents an exciting opportunity for enhancing flotation performance by enabling real-time monitoring and predictive control. Future research should focus on developing intelligent flotation systems that combine automated image analysis, real-time data processing, and adaptive process optimization to improve metallurgical outcomes.

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