Journal of Mineral and Material Science (JMMS)
ISSN: 2833-3616
Volume 4 Issue 1, 2023

Article Information
Received date : February 03, 2023
Published date: February 13, 2023

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DOI: 10.54026/JMMS/1054

Keywords
Machine Learning; Computer Vision; Object Tracking; Unsupervised Tracking and Hungarian Algorithm

Research Article

Flotation Froth Monitoring Using Unsupervised Multiple Object Tracking Methods

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Abstract

The popularity of computer vision algorithms applied to the metals and mining industry has grown drastically in recent years. This article will cover the application of computer vision models, video processing techniques, and methods of tracking many objects without data labeling (so-called unsupervised multiple object tracking) using the flotation froth, by example. In more detail, you will find in this article description of this kind of data domain as well as some words about the flotation process, the segmentation approach for many similar objects and an approach to its simultaneous tracking, an overview of existing tracking methods without data labeling and quality metrics comparison of these methods.

Introduction

Norilsk Nickel is the world's largest palladium and refined nickel manufacturer and one of the biggest platinum and copper producers. Our company devotes a lot of time and resources to production digitalization projects. Our data science team at Norilsk Nickel applies machine learning across the company's value chain. Because of the high economic impact on the company, one of the highest focuses for our team's work is the flotation circuit digitization (Figure 1). Let's look at this process in more detail on a particular example. The purpose of flotation is to separate valuable minerals from gangue during ore processing. Froth flotation is a method where this separation is based on the physical properties of the minerals. In a big flotation bank, ground ore (usually called a mineral slurry with a mix of water, the usual size of it is 0.1 - 0.2 mm) is mixed with water, air, and reagents. The hydrophobic ore particles of valuable minerals are attached to the formed froth bubbles. Bubbles recover upwards, and the remaining part of the ground ore descends (Figure 2), [1]. It is hard to achieve good separation characteristics in the only flotation bank. That's why the technology process usually consists of a series of flotation cells, one after another, forming a so-called flotation machine. For example, the concentration of copper may already increase from 2% to 4% after the slurry has passed through just one flotation machine. And you can have up to ten flotation machines to increase this concentration several times (Figure 3), [1]. The visual characteristics of the froth can tell us a lot about the physical [2,3] and chemical processes inside the flotation cell, which helps to optimize the overall control of the flotation process [4-11]. For example, looking for a froth speed, color, or bubble size distribution, the flotation operator can understand if she should add or decrease air, reagents, or slurry volume to achieve the highest metal recovery rate.

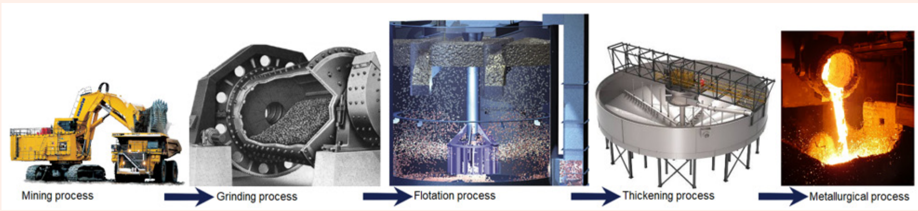

Figure 1: General technological process of Norilsk Nickel.

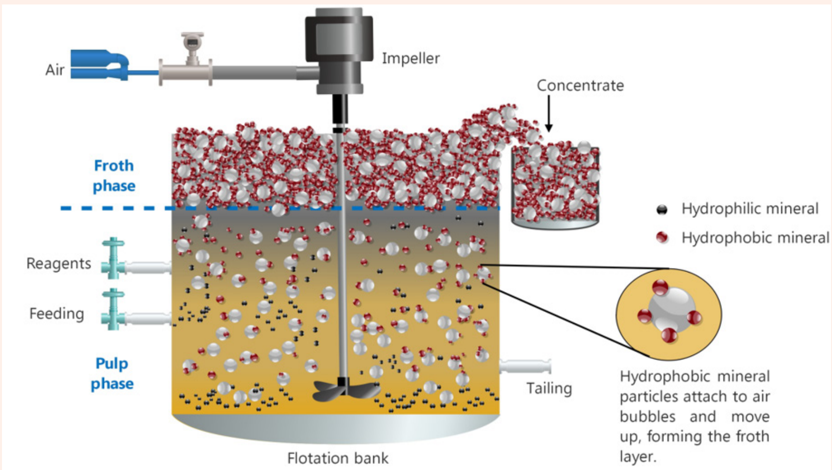

Figure 2: The working principle of the flotation machine.

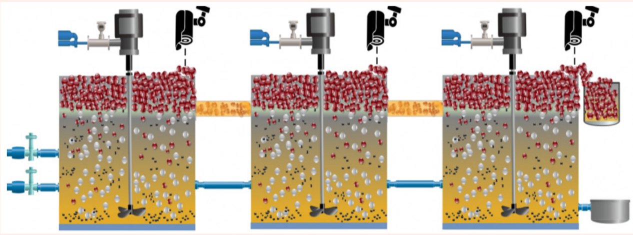

Figure 3: How the cascade of the flotation machine works.

Using computer vision methods in froth flotation monitoring is very helpful for technologists. It can significantly simplify process management, decreasing human factors and increasing overall concentrator recovery. For this reason, in one of our production facilities, video cameras were installed above each flotation cell (Figure 4) to monitor the state of the concentrate (more than 50 cameras and ten flotation machines in total).

Figure 4: Froth image camera view.

Problem Statement and Data Collection

Our task was to create a computer vision system capable of automatically processing video streams and determining the main foam parameters [12] in real-time. In addition, the number of objects (bubbles) could reach up to several hundred with almost no difference between the objects, and the system had to work on several dozen cameras at once. Therefore, we had to consider the problem of scalability and model optimization as well.

We had taken as the main features next froth parameters:

a. Bubbles size distribution;
b. The number of bubbles;
c. Bubbles type and form;
d. Bubbles lifetime;
e. Bubbles color;
f. Froth direction and speed;
g. Froth formation speed;
h. The type of froth flow (laminar/turbulent);

We used semantic segmentation for determining the bubble size, shape and the number of bubbles. We used the bubble tracking method to interpret froth direction and speed. We started from the premise that froth flow parameters directly depend on each bubble location change. Talking more about tracking task, it allows us to accompany a specific object in the video stream. In the simplest case, you need to recognize the object, determine its coordinates on neighboring frames, assign a unique identifier, and track its movement. We had many labeled data for semantic segmentation, and we even used synthetic data generation methods to get even more data for our model training. But we did not have enough labeled data for the bubble tracking task - just thirty seconds of videos. This data was not enough for model training, so we used it for model validation (Figure 5).

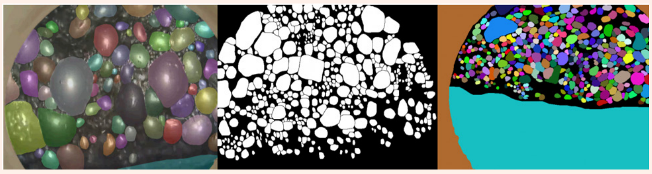

Figure 5: Examples of labeled data for segmentation task.

Unsupervised Tracking Methods

If there is no data for model training, it is better to look towards unsupervised tracking algorithms. Here is how it could work out:

a. You can extract features from any object in the picture. It could be physical dimensions, a chroma histogram, or non-interpretable features obtained by some mathematical transformation (function, algorithm, neural network, e.g.).

b. You can use machine learning or heuristics to find the objects in the picture. Detection and segmentation models require data labeling. Rules or heuristics can be based on the pre-assembled features of the object - the coordinates of its place on previous frames and mathematical laws of its movement.

c. If you want to track only one object, the task all comes down to finding this object on each frame.

d. If you want to keep track of many objects, the solution will also require matching the objects of your current frame to the objects on the next frame.

e. Object matching could be based on data labeling (it will be called supervised multi object tracking, but this method is not covered in this article) or on the correlation of the features without any labeling.

There are several approaches to solving unsupervised tracking problem [13] - Hungarian algorithm, Motion patterns, Simple Online and Real-Time Tracking (SORT) [14], Markov chains and Monte Carlo method [15], Optical flow-based tracking. We used most of them in our research and compared their efficiency on our data domain.

Froth Bubbles Semantic Segmentation

Before solving the bubbles tracking task, you must detect these bubbles on a frame. The data availability for segmentation allowed us to do both semantic segmentation and detection models. We had chosen semantic segmentation as information about the bubble shape could be helpful for the tracking model. Our data domain is similar to biological cells' data domain, as in the image below from the famous article (Figure 6), [16]. Therefore, we applied Unet architecture with ResNet18 encoder (pre-trained on ImageNet). During the training process, we heavily penalized the model for errors near or at the boundaries of the bubbles - so that the neural network tried to separate the masks of neighboring bubbles from each other. We used various algorithms for processing binary masks for automatic pixel search, for which we were giving significant penalties. We trained a model on the crops [17] with different augmentations. But for inference, we used the whole image as an input tensor. We can do this because our model has a fully convolutional architecture. As a result, we get a bubble segmentation model (Figure 7).

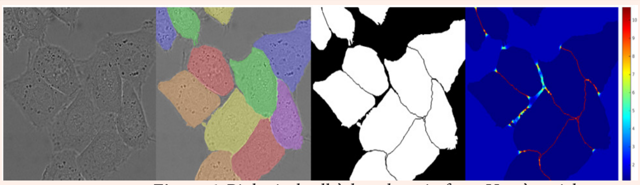

Figure 6: Biological cells' data domain from Unet's article.

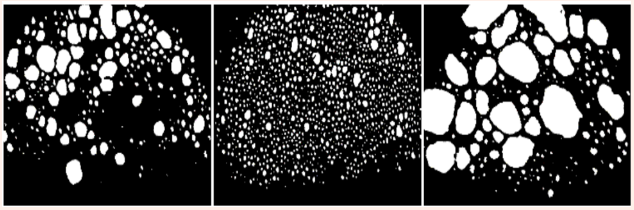

Figure 7: Demonstration of the segmentation model.

Simultaneous Tracking of Many Similar Bubbles

We trained the autoencoder architecture to use the bubble's shape as a feature. The encoder part of this model will convert the bubble mask into some embedding vector (or feature vector), which will store all information about the bubble's shape (Figure 8). The specificity of our data domain is a large number of bubbles in one frame, which are identical. On the one hand, this creates a challenge, though, on the other hand, it imposes some physical restrictions on the bubbles' movement. Bubbles cannot 'jump' over a neighbor or be blocked in the froth flow, but they can burst or collapse. Based on these patterns, we created the following plan:

A. Using the semantic segmentation model, we obtained bubble masks

B. Based on these masks, we extracted the features of each bubble for two adjacent frames. Quantitative features include center coordinates, width, height, and area. A qualitative feature of a bubble is its shape. We created a feature vector for each bubble using these bubble characteristics

C. We ran the Hungarian algorithm, which tries to find a pair of Yj from the second frame for each bubble Xi on the first frame. At the same time, to calculate the similarity matrix, we used a weighted sum of several metrics: for quantitative features - MSE, for form embeddings - cos_distance. We wrote down all found pairs in the dictionary: {Xi: Yj, …}.

D. The Hungarian algorithm could be inaccurate - it may match some bubbles on the first frame with the wrong bubbles on the second. Therefore, we filtered out anomalous bubble pairs using the following rules:

   a. The bubble cannot move a distance that is K times greater than the size of the bubble itself;

   b. The displacement of the bubble cannot be L times greater or less than the previous displacement, so it cannot sharply accelerate or slow down;

   c. The bubble cannot abruptly change the direction of its motion, i.e., the cosine distance between the vectors of the previous offset and the current one must not be less than the threshold G.

E. In the following images you can see the visualizations of our results (Figures 8 & 9).

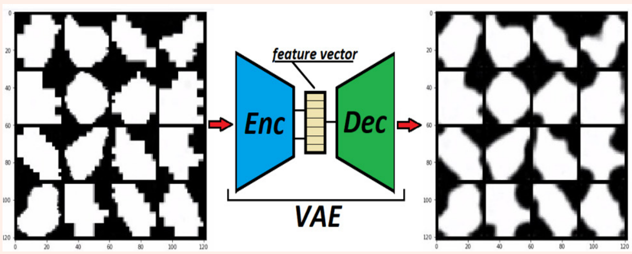

Figure 8: The working principle of the autoencoder.

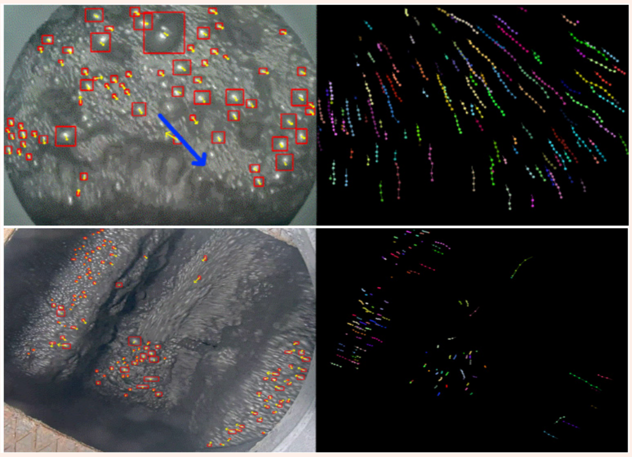

Figure 9: Tracking system visualization.

Results Comparison

Let us look at the following combinations of algorithms:

a. Alg1 - Hungarian algorithm (Quantitative features)

b. Alg2 - Hungarian algorithm (Quantitative features) and motion patterns

c. Alg3 - Hungarian algorithm (Quantitative features + bubbles form)

d. Alg4 - Hungarian algorithm (Quantitative features) + Kalman filter (SORT in other words)

Average quality metrics of bubble tracking algorithms on a small amount of labeled data (10 videos of different froth for 3 seconds each) and computational performance metrics on a test CPU (AMD Ryzen5 3600) you can see in Table 1 (and models visualization is on Figure 10). After averaging the speed of the bubbles, we obtain the overall froth speed. Let's compare each algorithm's predicted speed with the actual froth speed (Table 2). We will estimate the speed error using MAPE and the direction error - using cosine distance.

Table 1: Tracking metrics comparison.

Metric	Alg1	Alg2	Alg3	Alg4
HOTA	18.31	15.72	15.25	27.32
MOTP	65.17	65.22	65.36	64.92
OWTA	24.41	20.42	18.69	33.76
IDF1	13.16	8.88	9.54	20.29
IDSW	0.43	0.93	0.98	0.03
FPS	17.4	16.1	11.2	13.7

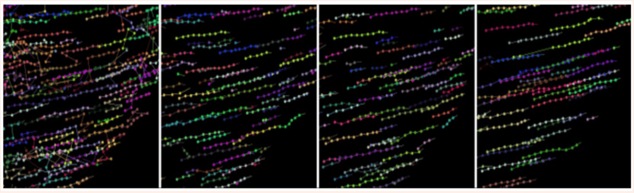

Figure 10: Output comparison of all algorithms (sequentially Alg1, Alg2, Alg3, Alg4).

Table 2: Speed prediction metrics comparison.

Metric	Alg1	Alg2	Alg3	Alg4
MAPE	0.201	0.183	0.178	0.131
COS	0.824	0.868	0.869	0.882

Conclusion

In our data domain, Alg4 leads in terms of quality metrics, and Alg2 leads in terms of quality-performance balance. The difference in performance between Alg4 and Alg2 is due to the Kalman filter requiring more computation than it does to check the conditions in the motion patterns.

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