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Performance of Convolutional Neural Networks for Feature Extraction in Froth Flotation Sensing

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Abstract: Image-based soft sensors are of interest in process industries due to their cost-effective and non-intrusive properties. Unlike most multivariate inputs, images are highly dimensional, requiring the use of feature extractors to produce lower dimension representations. These extractors have a large impact on final sensor performance. Traditional texture feature extraction methods consider limited feature types, requiring expert knowledge to select and may be sensitive to changing imaging conditions. Deep learning methods are an alternative which does not suffer these drawbacks. A specific deep learning method, Convolutional Neural Networks (CNNs), mitigates the curse of dimensionality inherent in fully connected networks but must be trained, unlike other feature extractors. This allows both textural and spectral features to be discovered and utilised. A case study consisting of platinum flotation froth images at four distinct platinum-grades was used. Extracted feature sets were used to train linear and non-linear soft sensor models. The quality of CNN features was compared to those from traditional texture feature extraction methods. Performance of CNNs as feature extractors was found to be competitive, showing similar performance to the other texture feature extractors. However, the dataset also exhibits strong spectral features, complicating comparison between texture feature extractors. The results gathered do not provide sufficient information to distinguish between the types of features detected by the CNN and further investigation is required.

Keywords: machine learning, soft sensing, computer vision, neural networks, data reduction

1. INTRODUCTION

Use of shallow neural networks in process engineering has proven promising. However, applications are generally limited to using neural networks as non-linear modelling tools for existing numeric process data. In the case of image processing, other machine learning methods are applied first as feature extractors due to the curse of dimensionality inherent in fully-connected networks as shown in Ali et al. (2015).

The emergence of deep learning has allowed the use of neural networks in applications which have previously been considered unsuitable. Specific hierarchies such Convolutional Neural Networks (CNNs) have been especially successful in image processing tasks and are of interest for extracting features from images and creating reduced representations as shown in Arel et al. (2010) and Ciresan et al. (2011). Such a feature extractor can be used in inferential sensing applications in the mineral processing industry.

In platinum extraction from mineral ores, froth flotation is a key process step in which froth appearance has been shown to correlate strongly with process conditions in Moolman et al. (1995). Amongst these conditions is platinum grade (fraction of total mass in a process stream or unit which is platinum). Platinum grade is difficult to infer from generally measured process conditions and cannot be measured directly in near real-time. This makes flotation froths an ideal case study for soft sensor design, allowing investigation of deep learning methods within soft sensors. Existing froth soft sensors are used primarily for measuring and controlling flotation cell conditions such as froth level, airflow, and mass-pull.

This article has three primary sections: Background, Methodology, and Results. In Background, relevant technical information of platinum processing, neural networks, and image-based soft sensors will be discussed. The Methodology section details parameters and methods used for feature extraction and the soft sensor; the outcomes of which will be discussed in the Results.

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2. BACKGROUND

Vision systems for flotation froths have been investigated for extracting bubble criteria such as size, shape, and velocity. Sadr-Kazemi and Cilliers (1997) show that these factors may be correlated to process conditions but are more commonly used to determine operating parameters for the froth flotation equipment rather than overall process performance.

Research in Moolman et al. (1995) has shown that the appearance of flotation froths is indicative of process conditions. Additionally, experienced plant operators have been able to determine process conditions based on visual examination of froths and past experience.

In process engineering, feature extraction methods used for vision systems include:

(1) GLCM - Grey-Level Co-occurrence Matrices. See Van Deventer et al. (1997)
(2) LBP - Linear Binary Patterns. See Steger et al. (2008)
(3) Wavelet transforms. See Peng and Chu (2004)

This work explores the usage of deep learning systems as feature extractors in comparison to these methods.

2.1 Platinum Flotation Process

Refining of platinum from ore is a complex multi-step process with a large number of interactions. Cramer (2001) indicates this is especially true for the flotation section; multiple flotation tanks cascade into each other with conservatively sized recycle loops and reagent dosages to ensure maximum recovery of platinum in the process.

Processed, finely ground platinum is suspended in water, forming a mineral rich slurry. This is fed into the froth flotation cells in which chemical conditions induce separation of platinum from waste material. The inefficiency of separation in a single cell is what requires multiple froth flotation cells to be used in the process.

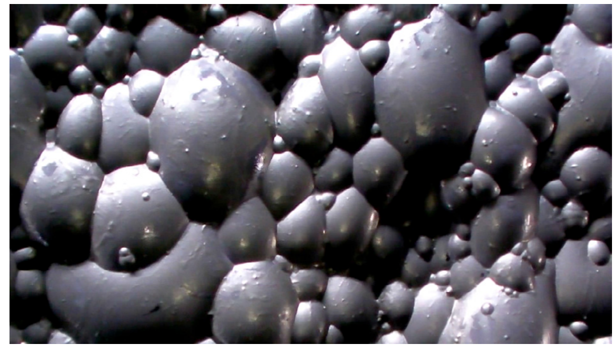
Plant operators aim to minimise inventory of platinum in concentrators (which is capital intensive on operations) while also maximising platinum grade in the final concentrate before smelting (lower final concentration results in more energy intensive smelting). Flotation cells are the last solid waste reduction stage and thus their performance is key to achieving these goals.

In Figure 1, example images of platinum froths can be observed. Both images are of the same flotation cell taken at different times, and thus under different process conditions. Some changes are apparent between the images, however, the meaning of these changes, and additional details not apparent, can only be determined by expert knowledge or through machine learnt correlations.

In Kistner (2013) it is shown that a suitably developed machine learning algorithm not only detects features apparent to human vision, but also hidden properties.

2.2 Inferential Soft Sensing

Kadlec et al. (2009) state that online and non-intrusive measurement are the prime advantages of inferential soft sensors. They are generally implemented to exploit standard process measurements such as temperature, pressure, pH, and more, to estimate process conditions that cannot be measured directly.



(a) Froth I

(b) Froth II

Fig. 1. Examples of flotation froth images exhibiting differing structures in the same process at different times and conditions

In Figure 2 the structure of a vision-based soft sensor is summarised. Images from the process are captured such as the flotation froth as shown in Figure 1. These are pre-processed to ensure uniform resolution and feature extraction is performed to reduce dimensionality. A model is generated to produce process information, in this work grade, from the extracted feature sets. This model is trained via machine learning using images correlated with previously collected and offline measured grade data.

Data-driven sensors (as is the case in image-based sensors) utilise empirical correlations between feature sets and process data. Conversely, fundamental sensors attempt to establish measured and inferred variable correlation through underlying physical and chemical relationships. This is not always possible for complex systems (such as image-based sensors) or where no fundamental relationships have been developed. Fortuna et al. (2007) indicate data-driven sensors are preferred in industry due to the difficulty in accurately modelling many chemical processes.

Feature Extraction Several feature extraction methods are compared in this work; in Figure 2, the feature extraction step is highlighted in green. Unlike other extractors tested, CNNs must be trained to generate a feature extractor before they can produce features. This training will occur separately from the soft sensor and is not represented in Figure 2. The feature extractors considered