AUTOMATED/SENSOR BASED SORTING RESEARCH AT CAMBORNE SCHOOL OF MINES

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Based on the Research of:

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Camborne School of Mines,
University of Exeter
OVERVIEW OF PRESENTATION

1. Sensor based sorting (overview)
2. Sensor development and strategies for pre-concentration of copper by Near-Infrared (NIR) radiation
3. Modelling separation efficiency using Monte Carlo Simulations
4. Combined CFD-DEM approach to modelling air ejection process (Removed for Website Publishing)
5. Other/Future Work
1. SENSOR BASED SORTING
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SORTING BASICS

• Sorting is one of the oldest and most innate technologies imaginable e.g. hand sorting by visual inspection

• Sensor-based sorters automate this technique

• Exploit measurable differences in the physical properties of particles, either natural or induced, to produce a distinct response to an applied force

(Manouchehri, 2003; Walsh, 1989)
1. SENSOR BASED SORTING

TOMRA SENSOR-BASED SORTER
1. SENSOR BASED SORTING

TOMRA SENSOR-BASED SORTER
1. SENSOR BASED SORTING

Air ejection system

• 128 MAC valves
1. SENSOR BASED SORTING

SORTING PROCESS

Input Feed

Feed Preparation

Particle Examination

Ejection System

Data Analysis

Particle Flow

Data Flow

Output Streams

(After Monouchehri, 2003)
1. SENSOR BASED SORTING

ADVANTAGES

• Removal of coarse waste reduces comminution and tailings disposal costs
• Reject low-grade material before transportation to the concentrator (in-pit, underground?)
• Higher mill feed grade – generally results in higher recoveries + increased production of concentrate
• Handle material over a wide size range - from 2 to 300 mm in diameter
1. SENSOR BASED SORTING

DISADVANTAGES

• Works best with closely sized feed (top/bottom size ratio of 2:1 - 3:1)
• Coatings (slimes, dust etc.) have adverse effect on surface based measurement
• Cost of compressed air – main consumable cost
• Have to distinguish particle from reference surface (belt, chute etc.) – colour choice important
• Single surface sensors only see one side of particle – potential for misplaced material
• Noise from air ejectors
1. SENSOR BASED SORTING APPLICATIONS IN THE MINERALS INDUSTRY

• Applications Include:
  – Uranium Ore
  – Quartz/Feldspar/Gypsum
  – Rubies & Sapphires
  – Carbonates
  – Coal
  – Diamonds
  – Gold
  – Talc
Performance/Separation Efficiency is a function of a sorting machine’s ability to:

- Generate sensor data which is representative of physical properties
- **Correctly** classify particles based on this sensor data
- **Accurately** and reliably actualise the separation of particles.
2. NIR SORTING FOR COPPER ORE
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NIR SORTING PRINCIPLES

• Near Infrared (NIR) is a region of the electromagnetic spectrum in the wavelength range of 780–2500 nm

• Two processes are responsible for the absorption of radiation of molecules in the NIR region
  – Electronic processes, and
  – Vibrational processes

• Research is focused on studying the vibrational processes of the NIR, where a limited number of functional groups (e.g. H$_2$O, OH$^-$ and CO$_3^{2-}$) dominates
2. NIR SORTING FOR COPPER ORE

NIR PROTOTYPE SYSTEM

Camera & AOTF crystal

Heraeus Noblelight lamps

60mm beam of light

Sample

Belt

Initial: 1160 mm, Final: 680 mm

AOTF NIR system (not to scale)
2. NIR SORTING FOR COPPER ORE

NIR SPECTRA

D = depth of feature

R = maximum reflectance

MRw = Maximum Reflectance wavelength position

W = feature width

Max R = Maximum reflectance of absorption feature

Min R = Minimum reflectance of absorption feature
2. NIR SORTING FOR COPPER ORE

NIR MINERAL COMPLICATIONS

• Within the NIR range, minerals can be grouped into three categories based on the absorption properties
  – NIR-active minerals displaying absorption features
  – NIR-active minerals not displaying absorption features
  – Non NIR-active minerals

• The visibility of absorption features of individual minerals in a spectra depends on any or the combination of these mineralogical factors:
  – NIR-active mineralogical composition
  – Relative proportion/concentration
  – Relative mineral accessibility or sensitivity to NIR radiation
2. NIR SORTING FOR COPPER ORE

APPROACH TO CURRENT RESEARCH

• Identify and discriminate copper-bearing minerals (chrysocolla and malachite) from their associated gangue materials

• Physical testing undertaken on prototype NIR sensor
  – Individual NIR-active minerals were crushed and ground to -45 µm particle grain size fraction
  – Mixtures were prepared at ratios of 1:9, 2:8, 3:7, 4:6, 5:5, 6:4, 7:3, 8:2 and 9:1 of mineral for two minerals mixture
  – Mixtures of three or more minerals were prepared at equal ratios of mass
2. NIR SORTING FOR COPPER ORE

SPECTRA OF MINERALS WITH SIMILAR FUNCTIONAL GROUPS
2. NIR SORTING FOR COPPER ORE

SPECTRA OF MINERALS WITH DISSIMILAR FUNCTIONAL GROUPS

Reflectance vs. Wavelength (nm)
- Malachite
- Kaolinite

Key wavelengths:
- Malachite: 1400 nm, 1415 nm, 1840 nm, 2210 nm, 2275 nm
- Kaolinite: 2200 nm, 2360 nm

Reflectance values:
- 0.0
- 0.1
- 0.2
- 0.3
- 0.4
- 0.5
- 0.6

Wavelength range:
- 1400 nm to 2400 nm
2. NIR SORTING FOR COPPER ORE
SPECTRA SHOWING INFLUENCE OF HEMATITE
## 2. NIR SORTING FOR COPPER ORE

### RESULTS OF TESTING

<table>
<thead>
<tr>
<th>Mineral 1</th>
<th>Mineral 2</th>
<th>Mass ratios of minerals</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1:9</td>
</tr>
<tr>
<td><strong>Minerals with similar functional groups</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chrysocolla</td>
<td>Muscovite</td>
<td>Muscovite</td>
</tr>
<tr>
<td>Chrysocolla</td>
<td>Kaolinite</td>
<td>Kaolinite</td>
</tr>
<tr>
<td>Chrysocolla</td>
<td>Chlorite</td>
<td></td>
</tr>
<tr>
<td>Malachite</td>
<td>Calcite</td>
<td>Mixed spectra</td>
</tr>
<tr>
<td><strong>Minerals with dissimilar functional groups</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chrysocolla</td>
<td>Calcite</td>
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<td>Malachite</td>
<td>Biotite</td>
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</tbody>
</table>
2. NIR SORTING FOR COPPER ORE

RESULTS OF TESTING

<table>
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<th>Influence of hematite on NIR-active features displaying minerals</th>
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</thead>
<tbody>
<tr>
<td>Mineral 1</td>
</tr>
<tr>
<td>-----------</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Chrysocolla</td>
</tr>
<tr>
<td>Malachite</td>
</tr>
</tbody>
</table>

<table>
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<tr>
<th>Complex mixture or associations</th>
</tr>
</thead>
<tbody>
<tr>
<td>-----------</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Hematite</td>
</tr>
<tr>
<td>Hematite</td>
</tr>
<tr>
<td>Chrysocolla</td>
</tr>
<tr>
<td>Malachite</td>
</tr>
</tbody>
</table>
2. NIR SORTING FOR COPPER ORE

PROJECT OUTCOMES

• In concentration-dependent mixture, the mineral with the higher concentration dominates spectra (e.g. chrysocolla and muscovite)

• In mineral accessibility-dependent mixture, even at lower concentration, the dominant mineral dominate spectra (e.g. malachite in chlorite)

• Minerals behave differently in different mixtures. A weak mineral in one mixture may be strong when mixed with another mineral
  – Chlorite and chrysocolla show features together appearing mixed. Chrysocolla dominates malachite mixtures, while chlorite features are almost completely captured by malachite.
  – Also, though malachite is weak in chrysocolla, it is stronger in hematite than chrysocolla.
2. NIR SORTING FOR COPPER ORE

PROJECT OUTCOMES

• Chrysocolla is only visible in hematite at 90 % concentration
• Only freely-occurring calcite can be targeted for discrimination
• Where hematite and chrysocolla occurs associated together, calcite, kaolinite and muscovite can be targeted for removal
• Malachite is relatively more NIR-active than hematite
• At higher calcite ratios both malachite and calcite show features side-by-side, but those of calcite appear displaced while malachite dominate when in higher concentration
2. NIR SORTING FOR COPPER ORE

NIR SORTING DECISION TREE

Copper ore

Determine mineral constituents and associations

A

Copper is NOT associated with high iron-bearing minerals (or other high-absorbing mineral)

I

Copper-bearing mineral contains a hydroxyl group (Chrysocolla)

Product:
NIR spectrum with features around 2270 and possibly 2160, 2200, 1400, 1415, 2265, 2360 and 1915 nm
Waste:
NIR spectrum with feature around 2340 nm

B

Copper is associated with iron-bearing minerals (or other high-absorbing mineral)

II

Copper-bearing mineral contains a carbonate group (Malachite)

Product:
NIR spectrum with features near 2275 nm with or without 1415, 2360 nm
Waste:
NIR spectrum with features around 2340 nm

III

Copper-bearing mineral contains a silicate (Chrysocolla) or carbonate (Malachite)

Product:
Featureless spectrum or NIR spectrum with features near 2270, or 2275 nm, with or without 1415 nm
Waste:
NIR spectrum with Features near 2200 and 2340 nm

IV

Iron-bearing mineral is finely mixed and disseminated or constituent NIR-active minerals reveal strong spectral mixing

Waste:
NIR is unsuitable as a sensing technique
2. NIR SORTING FOR COPPER ORE

CONCLUSIONS

In order to scope an application, a good understanding of the constituent minerals, minerals associations and the diagnostic features locations of the NIR-active minerals in the ore is essential. Hence, strategies outlined depend upon the copper ore type and character, and may need to be calibrated or modified for specific copper-bearing-mineral type to achieve optimal results.
3. MODELLING SEPARATION EFFICIENCY
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PROJECT RATIONALE

• Sensor-based sorting has been applied with good success in certain mining applications
• For the development of future applications it is important that the performance of sorters can be accurately predicted
• Development of a model which can be used to predict the effect of particle loading on the separation efficiency of a sensor-based sorter would therefore be beneficial
3. MODELLING SEPARATION EFFICIENCY

PERFORMANCE OF SENSOR BASED SORTERS

Performance/Separation Efficiency is a function of a sorting machine’s ability to:

- Generate sensor data which is **representative** of physical properties
- **Correctly** classify particles based on this sensor data
- **Accurately** and reliably actualise the separation of particles.
3. MODELLING SEPARATION EFFICIENCY

PARTICLE LOADING AND SEPARATION EFFICIENCY

• Distribution of particles determined by:
  – Throughput
  – Feed mechanism
  – Material Properties (size, shape)

• Effects of increased throughput
  – Physical properties masked
  – Co-deflection of particles ($R_c$)
3. MODELLING SEPARATION EFFICIENCY

Co-Deflection of Particles
3. MODELLING SEPARATION EFFICIENCY

APPROACH TO CURRENT RESEARCH

- Investigate the feasibility of using the distribution of particles to predict the fraction of co-deflected particles ($R_c$) and hence the separation efficiency of a sensor-based sorter
- Undertake physical testing on a Tomra Mining Solutions optical sorter to establish separation efficiency under varying test conditions
- Use computer models to predict the distribution of particles for the sorter and use these models to predict the separation efficiency
3. MODELLING SEPARATION EFFICIENCY

Test Sample

- Granite from Carnsew Quarry, Penryn, UK
- Split into fractions based on size and shape

<table>
<thead>
<tr>
<th>Test Sample</th>
<th>Particle Size Range (mm)</th>
<th>Particle Shape Category*</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>+15-20</td>
<td>Cubic + Flaky</td>
</tr>
<tr>
<td>B</td>
<td>+10-15</td>
<td>Cubic + Flaky</td>
</tr>
<tr>
<td>C</td>
<td>+6-10</td>
<td>Cubic</td>
</tr>
</tbody>
</table>

*Particle Shape Category Based on BS 812:105.1:1989 Flakiness Index

- Paint a portion of material to ensure identification of particles is 100% accurate
3. MODELLING SEPARATION EFFICIENCY

Physical Testing

• Tests undertaken at three throughputs -
  – 0.5tph, 1.5tph and 2.5 tph for the
    -20+15mm and -15+10mm fractions
  – 0.5tph, 1.0tph and 1.5tph fpr the
    -10+6mm fraction
• With three different compositions. 10%, 20% and 50% ‘reject’ material.
3. MODELLING SEPARATION EFFICIENCY METHODOLOGY

- A ‘Belt’ area (W x L) is defined by width of detection region and the test duration.
- The ‘Belt’ is split into discrete regions based on average particle diameter.
- The probability of there being a particle in a region determined by:
  - distribution of particles across detection zone
  - surface area occupied by particles
- Particles in adjacent regions used to estimate number of misclassified particles.

\[ W = \text{Width of Detection Zone (mm)} \]
\[ L = \text{Test Duration (s)} \times \text{Particle Velocity (m/s)} \]
3. MODELLING SEPARATION EFFICIENCY

RESULTS

-10+6mm

\[ y = 1.0164x \]
\[ R^2 = 0.9443 \]

-15+10mm

\[ y = 0.9406x \]
\[ R^2 = 0.921 \]
4. CFD-DEM MODELLING OF AIR EJECTION
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APPROACH TO CURRENT RESEARCH

• Approach
  – Use computational techniques to investigate the underlying physics of the separation
  – Model air jets using CFD, validated against physical measurements
  – Combine CFD data with DEM in a two-way coupling to model ejection process
  – Undertake physical testing on Tomra sorter to establish physical properties of air-jets and ejection process
Due to Current Research Project

• Slides removed prior to Publishing to MES Website by the request of Authors.
• Contact Exeter University for current information.
5. FUTURE/OTHER MINERAL PROCESSING RESEARCH
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OTHER RESEARCH INTERESTS AT CSM

• OPTIMORE project to optimize the crushing, milling and separation ore processing technologies for Tungsten and Tantalum mineral processing (www.optim-ore.eu)
  – Gravity separation modelling and optimisation
• Bio-hydrometallurgy applications for sulphide mineral extraction
• Further CFD-DEM modelling of sensor-based sorters
• NIR Sensor development and automated training methods
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