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Review

A Review of Sensor-Based Sorting in Mineral Processing: The Potential Benefits of Sensor Fusion

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Abstract: Sensor-based sorting techniques offer the potential to improve ore grades and reduce the amount of waste material processed. Previous studies show that sensor-based sorting can reduce energy, water and reagent consumption and fine waste production by discarding waste prior to further processing. In this literature review, recent investigations of sensor-based sorting and the fundamental mechanisms of the main sorting techniques are evaluated to inform optimal sensor selection. Additionally, the fusing of data from multiple sensing techniques to improve characterization of the sensed material and hence sorting capability is investigated. It was found that the key to effective implementation of sensor-based sorting is the selection of a sensing technique which can sense a characteristic capable of separating ore from waste with a sampling distribution sufficient for the considered sorting method. Classes of potential sensor fusion sorting applications in mineral processing are proposed and illustrated with example cases. It was also determined that the main holdup for implementing sensor fusion is a lack of correlatable data on the response of multiple sensing techniques for the same ore sample. A combined approach of experimental testing supplemented by simulations is proposed to provide data to enable the evaluation and development of sensor fusion techniques.

Keywords: sensor fusion; sensor-based sorting; ore sorting in mining and mineral processing; particle sorting; bulk sorting; simulation; X-ray fluorescence; X-ray transmission imaging; hyperspectral imaging; data synchronization

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1. Introduction

The mining industry is facing numerous challenges such as meeting rising global resource demand, declining ore grades and limiting environmental impact. The move to renewable energy sources, population growth, and global development are increasing the demand for most mineral resources [1–3]. Concurrently, the richest mineral deposits are being depleted leading to the development of low-grade/substandard ores, resulting in a continual reduction in the average grade of mined ore [4,5]. This requires larger volumes of lower grade ore to be mined and processed to meet rising demand [4]. The mining and processing of increased volumes of lower grade ore risks rapid increases in energy consumption and waste production at a time of increasing social expectations and legislative requirements to reduce the environmental impact of mining [4]. Overcoming these challenges will require the development of improved mining and processing techniques.

Selective mining and processing are approaches that can be used to more efficiently mine and process low grade ores [6]. Selective processing control can be implemented using algorithms based on sensor input which also provides the benefit of reducing potential human error [6]. Sensing techniques can provide real-time data that may be used to optimize production and reduce unnecessary processing of waste. Sensor based ore sorting provides a means of increasing processing efficiency and reducing tailings by diverting sub-economic material [7–9]. The early removal of mined material that cannot be processed economically avoids unnecessary grinding and flotation. This can significantly reduce the consumption of electricity, water, and chemical reagents, especially for low grade heterogeneous ores which contain high quantities of gangue. Additionally, by avoiding unnecessary grinding of gangue, the production of fine tailings is reduced. While the amount of mined material is not reduced, more of the waste rock remains at a coarse size, reducing the environmental impact from fine tailings which are difficult to contain [7–9].

Sensor-based sorting originated in the mid-20th century [8,9]. Most of the initial sorting machines separated the ore based on appearance and effectively automated traditional hand sorting techniques. A major reason for implementing this form of automated sorting was rising labor costs which made hand sorting uneconomic. In addition, the desire for greater security by having fewer people involved in handling the ore resulted in diamond mines being significant initial adopters of sensor-based sorting technology. Scientific advances, particularly in the fields of radiation, nuclear and fluorescence physics enabled new sensing techniques that could provide additional information on the sensed material [8,9]. These sensing techniques enabled the sorting of mined material based on characteristics other than appearance, allowing for the sorting of more ore types which could not be readily classified by appearance alone. The major sensing techniques used in mineral sorting are detailed later in this paper. The history of the development of sensor-based sorting, the principles of sorting particles based on sensor information and significant implementations of sensor-based sorting are detailed in a review and book chapters by Arvidson and Wotruba [7], Robben and Wotruba [8], and Chelgani and Neisiani [9].

The two main approaches to sensor-based sorting of mined material are particle sorting and bulk sorting. In particle sorting, individual particles of the mined material are sensed and characterized as either valuable or waste. The particles are then selectively ejected from the stream according to their classification. Note that it is possible either to eject the valuable particles or the waste depending on the expected proportions. In bulk sorting, parcels of bulk material transported on a conveyor belt are sorted instead of individual particles. The parcels are defined as the material transported on the belt for a given time, determined by the speed at which the material can be diverted within the system. Typical parcels consist of the transported material for a period between 30 s and a few minutes. As for particle sorting, parcels are classified as valuable material or waste depending on the sensor results and the material is then separated by diverting either the valuable material or the waste to a separate conveyer belt or stockpile.

The choice of particle or bulk sorting depends on the use case as each has strengths and limitations. Particle based sorting is more selective and can result in a higher upgrade of the ore quality. This is especially beneficial for ores with a high level of particle scale heterogeneity, where a small number of particles containing most of the valuable material are mixed with many barren particles, reducing the total grade. The main limitation of particle sorting is capacity, as the volume of material presented to the sensor must be sufficiently low to enable individual particles to be separated. Additionally, particle sorters typically can only handle a limited range of particle sizes, a maximum size ratio of approximately 3 between the smallest and largest particle is generally recommended for effective sorting [8]. Therefore, given the broad size distribution typically produced during blasting and crushing, the processed material must be separated by size into several streams before particle sorting. The capacity constraints and size range limitations result in a requirement for many particle sorters, operating in parallel, to provide sufficient capacity for a high output mine. As relatively small particles are sorted, the surface characteristics of the particles typically provide enough information for sorting the particles. This often allows surface sensing techniques to be used effectively for particle sorting. While surface sensors can be more affordable than bulk sensing techniques this is offset by the requirement for many sensors.

Bulk ore sorting, while not as selective as particle sorting, enables sorting decisions to be made for larger batches of material on a scale appropriate for high output mines. A single bulk sorter can process a high tonnage per hour corresponding to the output of a large scale mine. Bulk sorting is particularly amenable for the sorting of ore with a high level of heterogeneity on a medium scale with changes in the mined ore quality over a period of 30 s to a few minutes. A benefit of bulk sorting is that the separation techniques can handle a broad distribution of particle sizes. This enables the whole ore stream to be sorted without being separated by size range as would be required for particle sorting. As the entire ore flow is sorted together only one detector (per sensor type used) is required. However, given the large volume of ore being sorted, bulk sensing techniques are typically required to achieve sufficient sampling. While bulk sensing systems for bulk sorting often have a higher cost than the surface sensing systems commonly used in particle sorting, this is offset by the requirement for only a single sensor. Additionally, for relatively homogenous ore, results from the visible ore surface can provide a reasonable representation of the ore. Thus, for such ores, surface sensors can be sufficient for bulk sorting [10].

As has been discussed global resource demand is increasing while ore grades are declining. To meet demand without significant cost and environmental impact, improvements in mining and mineral processing technologies are required. Sensor-based sorting has been identified as a key technology which can help efficiently process large volumes of low-grade material as shown by case studies in previous reviews [7–9]. Determining the best sensing technologies and sorting technique for a mining operation is vital for the effective implementation of sensor-based sorting. In this work a literature review of state-of-the-art sensor-based sorting techniques in mineral processing is performed to provide information to help select the optimal sensor(s) and sorting technique(s) to process given ore types. The review results can also be used to evaluate the potential to combine data from multiple sensor types to better characterize the processed ore to improve sorting efficiency.

This review paper presents a comprehensive study of the literature for sensor-based dry sorting techniques and their recent applications. The potential to improve sensor-based sorting via sensor fusion techniques is also evaluated. In Section 2 of this review the literature search strategy is detailed and the main results of each identified study are tabularized along with key information such as the sensor and sorting type used, and the ore investigated. The fundamental bases of the main sensing technologies are detailed and this information along with the literature search results are used to analyze and discuss the capabilities and limitations of each sensor type for ore sorting. Section 3 of this review discusses the potential benefits of sensor data fusion. Based on the literature review and discussion of sensor capabilities several potential applications of sensor fusion in mineral processing and a classification of these applications are proposed. For each class of sensor fusion application, examples of their implementation in published works and/or potential applications are discussed. Finally, the challenges involved with implementing sensor fusion and potential pathways to overcome these challenges are discussed.

2. Review of Sensor-Based Sorting in Mineral Processing

2.1. Search Strategy

A search of the literature on sensor-based dry ore sorting was undertaken using the Scopus database. The Boolean search terms used to select potentially relevant papers are listed in Table 1. The abstracts of the papers identified by the Scopus search were manually checked to select papers appropriate for the review as detailed in Figure 1. The selected papers were then further examined. Additional papers of interest were identified from the references in the selected papers and were included in the review.

The scope of the review was chosen to cover studies of the implementation of sensor-based sorting techniques in mining operations, test work for the implementation of sensor-based sorting in a mining operation and development and testing of sensors for sorting. Sensing techniques that cannot provide data effectively in real time, i.e., providing data in a time period less than the sorting interval, were excluded from the study. For similar reasons sensing techniques for which sample preparation is required were also excluded. The review is limited to recent developments in the field of sensor-based sorting since 2017. For a review of earlier sensor-based sorting implementations see the review and book chapters by Arvidson and Wotruba [7], Robben and Wotruba [8], and Chelgani and Neisiani [9].

Table 1. Keywords for the literature search.

Search Term	Papers Remaining
sensing OR detector OR sensor	2,826,453
mineral OR ore	25,542
sort OR separat OR online OR on line	2249
NOT remote OR satel OR uav OR data mining OR sinter OR furnac OR soft sens OR mineral oil OR mineral water OR sensory	1361
Published in 2017 or later AND Language is English	383
Abstract examination	29

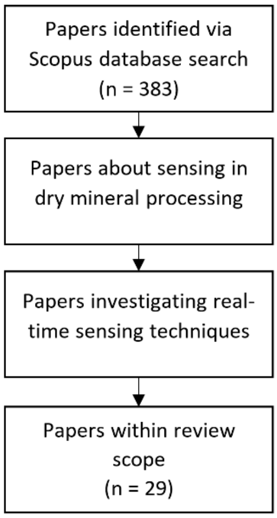

Figure 1. Flow chart of paper selection for literature review.

2.2. Review Findings

The literature review search found numerous recent studies investigating sensor-based ore sorting. The studies are summarized in Table 2, and include the sensor(s) used, the ore type, the sorting method, and the main findings. The reviewed studies are ordered within the table first by the primary sensor type used and then by the investigated ore. A majority of the studies investigated the use of X-ray Transmission (XRT), X-ray Fluorescence (XRF), Prompt Gamma Neutron Activation Analysis (PGNAA), Optical fluorescence or Optical reflection/absorption sensors. The reviewed cases using these main sensing techniques, the physical basis of the techniques and how this impacts sensor-based sorting are discussed in the following subsections.

The large number of recent studies indicates significant interest in the implementation of sensor-based sorting. Note that, due to commercial confidence concerns, many implementations and investigations of sensor-based sorting may not be publicly published. It is, therefore, likely that there are even more implementations and investigations of sensor-based sorting in mining operations than those detailed in this review. The uptake of sensor-based control in mining is increasing the likelihood of two or more sensors being used in a mining operation. This increased use of multiple sensors offers the potential to gain additional information from fusing the results from multiple sensor types. Sensor fusion is discussed in the later sections of this review.

Table 2. Summary of recent sensor-based sorting papers.

Sensor Type(s)	Ore/Material	Sorting Type	Findings	Reference
XRF	Copper porphyry ore	Particle (Test work) Bulk (Economic analysis)	Testing of six ore samples from different areas of two mines found varying efficiencies of XRF sorting. With a 0.3% Cu cut-off grade XRF sorting achieved recoveries of between 61% and 91% within 22% to 65% of the ore mass resulting in grade improvements of between 40% and 275%. Economic modelling predicted an increase in profit of between 20% and 151%, however, this is likely an overestimate as it is using particle sorting results evaluated with the costs for bulk sorting which would be less selective, particularly with a surface only sensor.	Nayak, Hitch and Bamber [11]
XRF	Copper ore	Bulk	Experimental test using low grade copper ore to evaluate the potential for using XRF sensors for bulk sorting. For 250 g samples it was found that 50 spot XRF measurements were sufficient to produce results within 2% of the bulk copper grade. Artificial 250 g material lots were produced with proportions of copper bearing particles ranging from 0% –100%. Surface XRF measurements of the lots were used to evaluate XRF bulk sorting. It was found that the XRF sensor results enabled rejection of 30% of the lots with the retention of 90% of the copper.	Li et al. [12]
XRF	Copper and silver ore	Bulk	Testing of XRF sensors installed over conveyors at operational mine sites showed that the sensors could measure the copper and silver grades of processed ore.	Oliinyk et al. [13]
Fluorine optical fluorescence sensor	Copper porphyry ore	Bulk	Experimental tests on fluorine crystal samples demonstrated fluorine specific up-conversion fluorescence. Tests on artificial samples made by combining a no-fluorine copper ore with fluorite showed that the sensor could measure fluorite content ranging from 1%–100%	Moffatt et al. [14]
XRT	Coal	Particle	Experimental tests found a correlation between XRT measurements and the specific gravity (R^2 = 0.83) and ash content (R^2 = 0.75) of the coal. This enabled estimation of the washability curve for processing the coal.	Zhang, Yoon and Holuszko [15]
XRT	Coal/Rare Earth Elements (REE)	Particle	Sampling from the XRT sorting plant showed that the sorters were able to separate the processed coal by ash content into high-grade and low-grade product and waste. Testing showed that REE content was correlated with ash content and that the XRT sorting upgraded the total REE grade in the discard by 21.3%	Akdogan et al. [16]
Dual Energy XRT	Copper ore	Particle	Tests on low grade, finely disseminated copper ore showed that sorting using high resolution XRT was able to extract 99.7% of the copper in 68% of the ore mass.	Kolacz [17]
Micro-CT and Dual Energy XRT	Copper	Particle	Experimental tests showed that micro-CT imaging could identify the copper content of particles and predict sortability. Pilot XRT sorting tests showed that 90% of the copper could be retained in 69% of the material mass.	Jin et al. [18]
XRT and LASER	Gold ore	Particle	Test work on a mine site demonstrated that sequential XRT and LASER based sorting was able to extract 88% of the gold from 50% of the mass. Financial modelling found that the use of sensor-based sorting reduced the cut-off grade from ~2.5 g/t to ~1 g/t.	Assis et al. [19]
Dual Energy XRT	Poly-metallic (Au, Ag, Zn, Pb) sulfide ore	Particle	Experimental assessment of XRT sorting potential for sulfide ore. 500 representative particles selected from run of mine ore were investigated using XRT. Archetype sample particles for both high grade ore and waste were chosen and used for material decomposition using XRT data. This resulted in a variable giving the similarity of the sensed particle to the high-grade ore particle or the waste particle. This was found to be effective for classifying ore and waste particles for sorting, with the potential to extract 90% of the sulfides in 55% of the mass.	Zhang, Yoon and Holuszko [20]

Table 2. *Cont.*

Sensor Type(s)	Ore/Material	Sorting Type	Findings	Reference
Dual Energy XRT	Rare Earth Element ore	Particle	Experimental tests showed that the XRT sensor was able to sort the REE ore particles into batches by grade. Setting various cut-off thresholds enabled the recovery of 68%, 89% and 96% of heavy REEs within 3%, 15% and 66% of the mass respectively.	Veras et al. [21]
XRT, NIR, Color, LASER	Rare Earth Element ore	Particle	Drill core samples were crushed and the grades of 107 selected particles were determined using ICP-MS. The effectiveness of each sensor type to sort the material into product and waste was determined for a 0.1% cut-off grade. It was found that XRT sorting was the most effective followed by LASER. Color and NIR sorting were not effective. Tests on a larger sample showed that XRT sorting could recover 98% of REE in 30% of the ore mass.	Cardenas-Vera et al. [22]
XRT	Rare Earth Element ore	Particle	Experimental tests and Monte Carlo simulations of artificial particle samples consisting of REE-bearing minerals and quartz were used to determine the effect of REE mineral grade on X-ray transmission. The experiments showed that the transmission was reduced progressively by 5%–30% as the REE grade was increased from 0.5% to 1%–5%. Simulations predicted roughly double the decrease which was attributed to oversimplification of the model. Both methods indicated XRT was well suited to REE sorting. It was also found that the heterogeneity of the XRT could be related to the REE grain size.	Neubert and Wotruba [23]
Dual Energy XRT and Infrared Imaging (SWIR)	Tin ore	Particle	Experimental tests showed that using SWIR imaging to detect chlorite content enabled sorting of skarn ore to extract 70% of the cassiterite while rejecting 75% of the gangue. Tests also showed that for mica schist ore, XRT-based density sorting enabled the extraction of 95% of cassiterite with rejection of 45% of the gangue.	Kern et al. [24]
XRT	Tin ore	Particle	Test work on ore samples determined that XRT-based sorting could extract 93% of the tin within 26% of the mass. When implemented on site it was found that the sorting extracted 90% of tin within 19% of the mass.	Robben et al. [25]
Dual Energy XRT	Zinc ore	Particle	Experimental tests showed that XRT sorting could extract 93% of the zinc within 70% of the mass.	Neto et al. [26]
PGNAA and XRF	Copper Gold Porphyry ore	Bulk (PGNAA) and Particle (XRF)	Test work on ore samples showed that PGNAA and XRF sensors were able to measure accurately the copper and gold content of the bulk ore and ore particles respectively. XRF sorting was able to extract 90% of the copper in 40% of the mass. Economic analysis evaluating the use of PGNAA bulk sorting to discard waste and select intermediate grade ore for XRF particle sorting found that the combined sorting could increase NSR by 6.5%.	Nadolski et al. [27]
Optical	Coal	Particle	Deep learning neural networks were able to sort high-grade coal from low-grade waste using optical imaging with a classification efficiency of 90%–96%.	Liu et al. [28]
Optical	Coal	Particle	Testing showed that machine learning based analysis of optical images enabled classification of coal into four different qualities with efficiencies of 78%–90% for a variety of algorithms. Using a majority vote of the algorithms improved classification accuracy to 92%.	Zhang et al. [29]
NIR	Copper ore	Particle	Testing of ore samples showed minimal NIR signal for copper minerals amongst iron bearing minerals while calcite showed a strong NIR signal. This indicated the NIR sorting could sort high carbonate waste from the copper ore.	Phiri, Glass and Mwamba [30]
Optical and XRT	Marble	Particle	Testing showed that optical sorting was able to classify particles as marble or waste with an accuracy of up to 85%–98% for particle sizes from 25–70 mm. XRT sorting was found to be ineffective due to the similar densities of marble and the host rock.	Paranhos et al. [31]

Table 2. *Cont.*

Sensor Type(s)	Ore/Material	Sorting Type	Findings	Reference
Optical	Mineral Sands	Particle	Experimental tests on mineral sands samples showed that machine learning based analysis of optical images was able to classify the mineral components of the sand with 91% efficiency.	Basu, Rao and Das [32]
Infrared Imaging (MWIR and LWIR)	Poly-metallic (Cu, Zn, Pb) sulfide ore	Particle	Tests demonstrated that the accuracy for classifying particles as ore/waste was up to 90%, 86% and 85% for the combined FTIR, MWIR and LWIR spectra respectively.	Desta and Buxton [33]
Infrared Imaging (VNIR, SWIR, MWIR and LWIR)	Poly-metallic (Cu, Zn, Pb) sulfide ore	Particle	Experimental tests showed that fusion of the results for all the measured IR spectra was able to be used to classify the particles as ore or waste with an accuracy of 87%–95% depending on cut-off grade (3%, 5%, 7%) and classification algorithm (K-means and SVC). Fused datasets provided an improvement of 0%–3% in classification probability over the best performing single spectra.	Desta and Buxton [34]
Infrared Imaging (VNIR and SWIR)	Tin ore and copper-gold porphyry ore	Particle	Tests showed that sorting based on machine learning classification of hyperspectral data was able to recover 90% of the desired metal in 27% and 43% of the mass for the tin and copper ore respectively.	Tusa et al. [35]
Inductive electromagnetic impedance sensor	Aluminum ore	Particle	Finite Element Method simulations of the sensor response to an ore particle model showed that the simulations were able to reproduce published experimental results by Tong et al. [36] and that the sensor response increased for higher aluminum grades. Simulated detector responses for a range of modelled ore particles were used as a dataset to train a neural network classification algorithm to sort the material into waste and product based on an aluminum cut-off grade of 2%. Testing of the algorithm found that ore and waste were classified correctly 82% and 97% of the time respectively.	Li et al. [37]
Camera based particle size distribution sensor	Copper ore	Bulk	On-site tests showed that the sensor could extract the sizes of 60% of the visible large (20 mm–250 mm) particles on the surface of conveyed copper ore. The particle size distribution could be found for particle sizes over 20 mm.	Leiva, Acuña and Castillo [38]
Gamma Activation Analysis	Gold ore	Bulk	Experimental tests demonstrated that the GAA sensor could accurately measure the gold grade of ore and concentrate samples for gold concentrations from 0.1–4000 ppm	Tickner et al. [39]
Microwave Imaging	Gold and silver ore	Particle	The microwave imaging response to sample ore particles built from micro-CT and QEMSCAN data was simulated. It was found that the imaging technique could detect even small inclusions of the highly conductive gold and silver.	Duan, Bobicki and Hum [40]

A wide range of sensing technologies have been used, or considered for use, in sensing of ore characteristics for sorting and processing control. Most sensing techniques involve exposing the examined ore to electromagnetic radiation, both ionizing and non-ionizing, and sensing a response from the material to help identify its properties. The fundamental principles of each of the major techniques are discussed below.

2.2.1. X-ray Fluorescence (XRF)

In XRF sensing, the investigated ore is irradiated with incident X-ray photons. The incident X-ray photons interact with the bound electrons of the ore resulting in the excitation and ionization of the bound electrons. This results in a vacancy among the orbital electrons which can be filled by a higher energy electron. The transfer of an electron from a higher energy state to a lower energy state results in the emission of a photon with an energy equal to the difference between the electron energy levels. The energy of the emitted photons is characteristic of the energy gaps and hence the isotope of the material with which the initial photon interacted. The resulting emitted X-rays are known as characteristic X-rays due to this association. The X-ray energy spectrum emitted from the sensed material is sensed by a photon detector. The relative contribution from different characteristic X-rays can be used to determine the elemental composition of the sensed ore. Note that the energy gaps between orbital electron energy states are typically below 1 MeV. Therefore, the emitted X-rays are of a relatively low energy with limited penetration potential. Hence, the observed photon signal is primarily from the surface of the sensed material.

Several studies of the use of XRF for sensor-based sorting were identified in the review [11–13,27]. All of these studies investigated the sorting of copper ore due to the strong response of XRF to the copper grade [13]. Due to this strong response, it was found that XRF sensing was capable of effectively sorting copper ore with typical recovery of ~90% of the Cu within 65%–70% of the input mass [11,12]. While XRF is a surface sensing technique and as such is typically used for particle sorting it was found that for relatively homogenous material that XRF is also suitable for bulk sorting [10,12]. Overall, XRF is a capable sensing technique for sorting any material for which the element of interest has a strong XRF response. Particle sorting is primarily used due to XRF being a surface sampling technique, however bulk sorting is also feasible for more homogenous ores.

2.2.2. X-ray Luminescence (XRL) and Optical Fluorescence

In XRL and Optical Fluorescence, low energy X-rays and optical photons, respectively, are used to irradiate the investigated ore. Due to the lower energy of the incident photons compared with XRF, the electrons of the ore are not ionized, instead some of the higher energy bound electrons are excited to a higher energy level. The excited electrons will return to their original ground state with consequent photon emissions with energies corresponding to the difference in energy between the energy levels involved in the transitions. The energy spectrum of the emitted photons is scored and the relative contribution to the spectrum from each characteristic energy provides information on the sampled material. The higher energy level transitions that are investigated are located at a greater distance from the nuclei of the excited atom than for XRF and are therefore affected by the adjacent nuclei within the investigated material. This results in the sensor response being representative not only of the excited elements, but also their interactions with nearby elements, and therefore the mineralogy of the investigated material. This is the key difference compared to XRF where the higher energy photons used ionize bound electrons from lower energy levels. These lower energy levels are closer to the excited atoms' nuclei and therefore are not significantly affected by the chemical state of the material. This results in XRF providing information on the elemental composition. For XRL and Optical Fluorescence both the photons used to excite the material and the resulting photon emissions have relatively low energies and hence poor potential to penetrate the observed material. This results in the sampling being limited predominantly to the surface of the sensed material.

As XRL based sorting is a well-established technique in diamond mining operations [8], no recent publications of the technique were found. However, there is interest in developing optical fluorescence sensors for detecting minerals of interest to enable sorting. This was shown in the study by Moffat et al. [14] where a fluorine fluorescence sensor was developed. These fluorescence sensors can excite and induce a characteristic response for a target mineral enabling its abundance to be accurately measured. Note that a requirement for florescence sensing to be feasible is that the target mineral must have a fluorescence response, limiting the minerals for which the sensing technique is suitable. Additionally, noise from other components of the sensed material and varied response strength of the targeted mineral results in the requirement of extensive calibration of the technique for each specific ore type.

2.2.3. X-ray Transmission (XRT)

In XRT sensing, the studied material is irradiated with an X-ray beam. The transmission of the incident X-ray photons through the material is measured via a photon detector, beyond the sensed material, in the path of the X-ray beam. Given the known energy and flux of the incident X-rays, measurements of the photons penetrating the material enable the transmission of the photons through the material to be determined. Information on the sampled material can then be calculated from the transmission which is a measure of the probability of the incident photons interacting with the material. The probability of an incident photon interacting with the material depends on three factors, the thickness of the material the photon passes through, the density of the material and its effective atomic number. The effective atomic number is the equivalent atomic number of a single element material that would have the same photon interaction probability as a material consisting of different elements. The first two parameters determine how much material the photon must pass through while the third affects the probability of some photon interactions occurring. By using two incident X-ray energies which have different interaction probabilities and hence transmission through the material it is possible to correct for the unknown material thickness and determine a combined density/atomic number value. This enables separation of material based on density/atomic number. Due to the transmission of the photons through the entirety of the investigated material the observed results are representative of the entire bulk volume of the material.

The review identified numerous studies of XRT sensor-based sorting [15–26,31]. It was found that XRT sorting was effective for a wide variety of ore types including coal, copper, rare earth elements, tin and zinc. XRT sorting is suitable for sorting any material where there is a difference in the density/atomic number between the desired component and the waste material. This was demonstrated by the failure of XRT sorting for a marble mine shown in a study by Paranhos et al. [31] resulting from minimal differences between the densities of the marble product and the waste rock preventing effective sorting. The studies showed that XRT particle sorting can typically extract 90%+ of the desired product within 20%–70% of the processed mass. While the sorting is highly ore dependent there was a general trend for more effective sorting for material with a greater density separation between the desired product and waste such as for rare earth element ores. Despite XRT being a bulk sensing technique for all the reviewed studies particle sorting was evaluated. This is likely due to the high selectivity of particle sorting combined with greater thickness uncertainties for bulk volumes of material. Additionally, particles can be penetrated by lower energy X-rays, reducing shielding requirements.

2.2.4. Prompt Gamma Neutron Activation Analysis (PGNAA)

In PGNAA, the investigated ore is irradiated with neutrons. The incident neutrons interact with nuclei within the material and are captured by the nuclei. In these neutron capture events, compound nuclei are produced from a combination of the original nucleus and a captured neutron. The newly formed nuclei are in highly excited states due to the release of the binding energy from captured neutrons. The excited nuclei then return to the ground state via the emission of gamma photons with energies corresponding to the energy gaps between excitation levels of the nuclei. Hence, the energies of the emitted gamma photons are characteristic of the nuclei of the investigated material. The energy spectrum of the emitted gamma photons is scored by a photon detector. The spectrum is used to determine the elemental composition of the material from the relative intensities of the characteristic gamma photon emissions. The emitted characteristic gamma photons have energies typically within a range of between 2 and 12 MeV. These high energy photons are highly penetrative, which combined with the high penetration of the incident neutrons allows for effective sampling of a large volume of bulk ore. Note that the characteristic emissions are from the energy levels of the nucleus instead of the energy levels of the bound electrons as is the case for most other sensing techniques. This is beneficial as while the chemical state of the atom can alter the electron energy levels, the nucleus energy levels are unaffected. This results in PGNAA being able to determine the elemental composition of the material. However, due to the limited impact of the chemical state for PGNAA, additional sensor results would likely be required to determine the ore mineralogy in addition to the elemental composition.

The PGNAA sorting study identified within the review demonstrated that PGNAA was able to accurately determine the Cu grade for bulk material. The ability to accurately determine the concentration of a range of elements within bulk material enables PGNAA to be effective for bulk sorting material where the elements of interest have a measurable PGNAA response [41]. As the PGNAA signal is sampled from the entire bulk volume PGNAA is not suitable for particle sorting. However, as shown in the study by Nadolski et al. [27], it is possible to use PGNAA to select the feed to a particle sorter using another sensing technique. This enables particle sorting only for the material most amenable to upgrading via the technique, reducing capacity requirements and avoiding unnecessary processing.

2.2.5. Optical and Hyperspectral Imaging

In optical imaging a photon source is used to illuminate the sensed material. The energy spectrum of the photons reflected from the material is detected and compared with the spectrum used to illuminate the material. This enables the determination of the reflectance and absorption of the incident photons by the material across the measured energy spectrum. The absorption profile is indicative of the mineralogy of the sensed material. However, different minerals can have similar absorption profiles. This can complicate unique identification of the mineralogy present. Therefore, additional information from geological knowledge or other sensors is often required to enable identification of the material's mineralogy. There are a wide variety of sensors that use the principles of optical imaging over a wide spectrum of photon energies from infrared to ultraviolet, utilizing a range of photons sources such as LEDs and lasers. While most sensors only use a portion of the photon energy spectrum, it is possible to conduct absorption/reflection studies over multiple sections of this spectrum using a technique known as hyperspectral imaging. Using data from a broader spectrum of photon energies typically enables better determination of the mineralogy of the sensed material. However, for some applications a subset of the spectra is sufficient to capture a response characteristic of the material and limited additional information can be gained by considering a broader spectrum. As the low energy photons used in optical imaging techniques are unable to penetrate the sensed material, the sampling is primarily from the surface of the material.

Numerous studies of sorting using optical/infrared imaging were identified within the review [19,22,24,28–35]. It was found that optical and infrared imaging were suitable for sorting a wide range of ores including coal, copper, gold, lead, marble, mineral sands, rare earth elements, tin and zinc. It was found from particle sorting tests that optical/infrared imaging was capable of correctly sorting ore and waste particles with a typical efficiency of 80%–95%. This resulted in being able to extract 70%–90% of the desired material within 25%–50% of the mass using optical sorting. Optical sorting is suitable for material where the mineral of interest has a characteristic absorption response for the light spectrum used. Note that when sorting based on elemental grade is required, the primary mineral containing the element of interest can be used as a proxy for optical sorting. However, this approach can cause some of the desired element not within the primary mineral bearing the element to be discarded as waste when sorting. Additionally, as optical sensing is limited to the visible surface, ore particles can be incorrectly discarded as waste if the present target mineral is not expressed on the surface of the particle. These factors can result in lower recovery and higher mass discard compared with bulk sensing and less mineral specific techniques such as XRT as shown in the investigation by Kern et al. [24].

3. Sensor Fusion

Sensor fusion is the use of data from two or more sensor types to provide additional information on the sensed material compared to a single sensing technique in isolation. This can enable more efficient material sorting and feed-forward process control. Sensor fusion is beneficial as each sensing technique has its own strengths and limitations. Therefore, combining different techniques can help combine the strong points of each while reducing the limitations of the sensing techniques. Additionally, sensing techniques often provide different types of information, which combined provide more detail to enable identification of the ore mineralogy.

3.1. Sensor Fusion Classification

Several approaches to fusing data from multiple sensors for sorting in mineral processing can be identified based on the analysis and discussion of sensor types and sorting techniques in the previous sections. These approaches involve varying degrees of combination of data from different sensor types. A classification system is proposed that can separate applications of sensor fusion for sorting in mineral processing into four distinct classes depending on how the sensor information is used and to what degree the sensor data are combined. These classes are defined and discussed below and are presented in order of the degree of data combination from greatest to least.

The first class consists of full sensor fusion to improve mineral identification. In this class, data on the characteristics of the sensed material from two or more distinct sensor types are combined. This enables more information on the ore mineralogy to be determined than could be provided by each sensor type individually. This additional information can be used to improve the classification of the mineralogy of the processed ore as well as the sorting of the processed material into a product for further processing and waste to be discarded. Sensor fusion can be performed at both a high and a low level. For high level sensor fusion, the data from each sensor are processed individually and the combined results from each sensor are used to identify the ore mineralogy. In low level data fusion, the data from each sensor are combined and the data are processed together to provide additional information on the sensed ore. Note that low level fusion is difficult using standard data processing techniques, given the difference in data types for most sensors. However, it may be possible to analyze the combined data set from multiple sensors using machine learning techniques to enable classification of the sensed ore mineralogy.

The second class consists of the fusion of the primary sensing technique with a secondary technique which provides similar data to the primary technique. The secondary sensing technique is used to supplement the results from the primary sensor for cases where the primary sensor is ineffective. For this class, the secondary sensor is not providing a different type of information but is only providing information instead of the primary technique. This can be necessary because each sensing technique has varying sensitivity to the components of the material, based on the suitability of the components for each given sensing technique. Most sensing techniques will have cases for some minerals or elements where the sensor provides a poor response. By combining multiple sensing techniques that provide similar information on the material, it is possible to overcome the sensitivity limitations for each individual technique.

The third class of sensor fusion consists of using results from a secondary sensor to aid the processing of results of a primary sensor. This differs from full sensor fusion as described in the first class as all the information on the sensed ore is derived from the primary sensing technique. The secondary sensor data are used only to assist with the processing of the primary sensor data. This is beneficial for sensing techniques where it can be hard to resolve the observed data to determine precisely the characteristics of the sensed ore.

The fourth class of sensor fusion consists of using multiple sensors to sequentially sort the material based upon the individual sensor results. In this class, each sensor-based sorting step selects the ore for later sensor-based sorters to process. This can be done by selecting a portion of the processed material that is suitable for further sorting or by removing material that could reduce sorting efficiency. This allows for selection of the optimal feed material for later sensor-based sorting. Note that while multiple sensors are used for ore sorting, the results from the sensors are not directly combined.

3.2. Sensor Fusion Examples

Several papers have considered sensor fusion, and these are summarized and discussed below. Additionally, given the limited number of studies on sensor fusion, several potential sensor fusion applications are also proposed and discussed to illustrate potential applications of each class of sensor fusion.

A study by Desta and Buxton [34] conducted an investigation of class 1 data fusion for infrared sensors. Data from several infrared sensors, each covering sections of the infrared spectrum, were combined to provide information on the reflectance and absorbance of the material across the entire infrared spectrum. The combined dataset was then analyzed using machine learning classification algorithms to sort the poly-metallic (Cu, Zn and Pb) sulfide particles into product and waste. The fused dataset covered a broader spectrum providing more information to aid classification, improving the correct classification probability by up to 3% compared with the data from a single section of the IR spectrum. While this is a good example of techniques involved in data fusion, only limited additional information is gained due to fusing two similar sensors based on the same fundamental technique. This limits the potential for additional information to be gained on the sensed particles.

A potential application of class 1 data fusion using distinct sensor types would be the fusion of hyperspectral sensor data with sensors that can measure the elemental composition of the ore such as PGNAA or XRF. The fusion of these sensors is beneficial as each sensing technique can provide complementary information which can improve the processing of the data and provide more comprehensive information on the sensed ore. The hyperspectral reflectance/absorbance spectrum observed from the sensed material can be used to detect some mineralogy. However, the spectra for some minerals can be similar, making precise identification difficult. Information on the elemental composition of the sensed material from a PGNAA or XRF sensor can help to limit the range of potential minerals, improving the classification of the mineralogy based on hyperspectral data. Knowledge of the mineralogy of at least part of the sensed material from the hyperspectral analysis can also assist ratiometric analysis of the elemental composition data from PGNAA or XRF sensors, enabling the extraction of additional data on the mineralogy of the sensed material. This potential application of sensor fusion could enable the extraction of more information than the use of both sensor types individually, providing greater information on the elemental composition and mineralogy of the sensed ore which would enable more effective ore sorting. Note that the varied sampling distributions of different sensing techniques complicate the combination of data from multiple sensor types as considered in this example. It would be difficult to combine data from a surface only sensing technique such as hyperspectral imaging with a bulk sensing technique such as PGNAA. While it is easier to combine hyperspectral data with XRF, which is also surface sampling, information on the bulk volume of the material would not be available. The combination of differing sampling distributions is discussed in later sections of this paper.

An example of a sensor designed for class 2 sensor fusion is the fluorine fluorescence sensor developed by Moffatt et al. [14]. This fluorine specific sensor was able to accurately measure the fluorite content of a copper bearing ore. The sensor was developed to complement PGNAA analysis, a technique which has poor sensitivity to the fluorine content of the sensed ore. The combined PGNAA and fluorescence sensors can detect the elemental composition of the ore, including fluorine. This application of sensor fusion can help improve the utility of PGNAA based ore quantification and sorting for ores where the fluorine content is an important indicator of difficulties in ore processing or the ore grade.

A potential application for class 3 sensor fusion would be to assist the processing of data from XRT sensors that measure the X-ray transmission to determine the density/atomic number of the sensed material. In XRT sensing, the thickness of the sensed material plays a key role in the transmission. This means that it is typically not possible to determine precisely the thickness, density and effective atomic number of the material even with measurements at numerous X-ray energies for a 2D image [42]. Other sensing techniques, such as a 3D camera or LIDAR, can provide information on the thickness of the sensed ore. This information can be used when analyzing XRT data to resolve the thickness uncertainty. With a known thickness, it would be possible with measurements at multiple X-ray energies to provide a better determination of the density and the effective atomic number of the sensed material. The density and atomic number can be separated using the change in relative probability of different types of photon interaction with photon energy. This is due to the interaction types having varying sensitivity to the atomic number of the material [43]. Determining the density and atomic number of the sensed material can enable better identification of the ore mineralogy [42].

An example of class 4 sensor fusion was reported in the investigation by Nadolski et al. [27], of the use of a combination of PGNAA and XRF sorting for upgrading a copper-gold porphyry ore. It was proposed to use a PGNAA sensor for bulk sorting of the mined product into waste, which is discarded, low-grade ore which undergoes particle sorting using XRF sensors to improve the grade and high-grade ore which is sent directly to the mill. In this implementation, the PGNAA sensor is used to select the feed for XRF particle sorting, ensuring that only low-grade ore, which will benefit the most from upgrading, is sent to the particle sorter. This enables a reduction in the required particle sorting capacity while still delivering most of the potential economic return. Economic modelling of the combined PGNAA and XRF sorting predicted a 6.5% increase in net smelter return.

Another example of the implementation of class 4 sensor fusion was presented in the study by Assis et al. [19], where particles of a sulfide gold ore were sorted using both XRT imaging and LASER reflection sensing. In this case, the sensors were used individually to sense different characteristics of the ore associated with gold enrichment. The LASER sensor identified quartz bearing ore particles, while the XRT sensor identified denser particles associated with sulfide mineralization. The sorting was done sequentially based on each technique to select ore particles with characteristics indicative of higher gold grades for further processing. The initial XRT sorting removed denser ore particles with sulfide mineralization, reducing the material required to be sorted by the LASER sensor. Sorting particles based on an individual sensor results in discarding particles that have some quartz mineralization and some sulfide mineralization just below the cut-off for each sensor type despite the potential for an economic gold grade. This suggests that a higher level of fusion of the data from each sensor could potentially increase the gold recovery.

3.3. Limitations on Implementing Sensor Fusion

The presented literature review of sensor-based sorting in mineral processing has shown that, while sensor-based ore sorting and characterization is of growing interest and has been investigated for numerous mining operations, few studies have considered the use of two or more sensor types. Furthermore, even when the use of multiple sensor types is considered, there has been no or only limited investigation of the potential fusion of these different sensor types. From the review findings several potential factors limiting the investigation and implementation of multiple sensor types and data fusion have been identified. These factors are discussed along with potential avenues to overcome these issues to enable the progression of sensor fusion development and implementation.

A major reason why the consideration of multiple sensors is limited, is that prior to adoption of a sensing strategy for a mining operation, it is typical to send an ore sample for testing and evaluation of the sorting potential of the ore for a given sensor of interest. However, this testing is typically performed by a research group or sensor manufacturer that has expertise on only one sensor type. As a result of this, mining operations that choose to acquire sensors typically acquire one sensor type at a time, with limited consideration of sensor fusion. This results in very few mining operations with multiple sensor types installed, limiting the availability of data from multiple sensors which can be evaluated for fusion potential.

Another challenge to evaluating the potential for sensor fusion is the availability of correlated and comparable data. Even in the case of mine sites with two or more sensor types installed, it is not sufficient to have the data from each sensor type available, the data must be able to be compared. There are numerous potential difficulties in comparing sensor data. Only sensors located at the same position on the mine site can generally be compared effectively. This is due to the mixing of ore through stockpiles and during transport, as well as changes in the condition of the ore during crushing and grinding. These changes in the ore prevent sensor information from different locations being directly compared as different distributions of the ore would be presented to the sensors.

Even when the same ore is presented to multiple sensors, this is not sufficient to ensure direct comparability between sensors. It is also important to consider, and correct for, the temporal and spatial sampling of the ore. Different sensors can have different sampling time intervals, which results in data from the sensors being not directly correlatable as different volumes of ore passed the sensors for each sample period. Another issue is that different sensing techniques have different spatial sampling distributions. Sensors can sample a 'spot', a minute volume on the surface of the material, the entire visible surface of the material or the bulk volume of the material. This typically limits direct comparison of results from bulk, surface and spot sensors because the sensor results are from different spatial samplings of a heterogeneous material. Furthermore, even for the same sampling distribution there can be differences in the distribution of the extracted data. For example, both PGNAA and XRT are bulk sampling techniques, however PGNAA provides results for the entire sampled volume while XRT typically provides a 2D image of the transmission through the bulk volume. This can cause additional difficulties in comparing the sensor results. Additionally, even if the same sampling type is used, there can be differences in the field of view and spatial sampling bias for different sensors that can still result in complications in comparing the simulation results.

Another challenge when sorting material via the use of fused data, is determining the uncertainty of the combined dataset. Every sensing technique involves some level of uncertainty within the output data which must be considered when making an operational decision based upon said data. When multiple sensor sources are used this can compound the effect of uncertainty as the uncertainty within each individual sensor measurement is combined within the fused dataset. This results in the possibility for fused data that any individual sensor type and any potential combination of sensor types could be giving an erroneous response which does not reflect the processed material. As such, any processing of the fused dataset should take this possibility into account when making control decisions.

3.4. Pathways to Implementing Sensor Fusion in Mining

In the previous section, numerous challenges in the implementation of sensor fusion for mining applications were identified. These challenges are not insurmountable and have the potential to be overcome through improved interdisciplinary collaboration and an increased uptake of techniques new to mining applications. Potential approaches to help overcome the issues of data availability, data synchronization and data analytics and hence achieve sensor fusion are proposed and discussed in this section.

3.4.1. Data Availability

Availability of correlatable data from multiple sensor types to aid evaluation of optimal sensor fusion combinations is key to the development and implementation of sensor fusion techniques. As discussed in the previous section, most mining operations evaluate and acquire one sensor type at a time. However, given the growing interest in sensor-based sorting and control, gradually over time more mine sites will acquire multiple sensors providing valuable data for evaluating the potential for sensor fusion. As data from mining operations is currently limited, testing of the response of multiple sensor types for a range of ore archetypes should be performed to enable a timely evaluation of sensor fusion potential.

An optimal approach to producing high quality data for evaluating sensor fusion requires the close co-operation and integration of multiple research teams across various disciplines, each with expertise in a specific sensor or sensor class. The combined knowledge would enable effective evaluation of the sensor response to an ore type for a wide range of sensors. Traditionally, experimental tests have been used to evaluate sensor response, however it can be difficult to ensure correlatability of the experimental results. While each team could perform experiments on the same material sample to ensure correlatability, it would be difficult and time consuming to ship the same sample to numerous research groups for each to perform a sensor evaluation sequentially. Additionally, it would be difficult to ensure that the sample investigated by each research group consisted of the same material in the same presentation, given the disturbances of the sample and potential for loss of, and damage to, the sample during multiple stages of transport and handling.

A promising technique to help overcome the difficulties involved with ensuring that each research team receives the same sample to ensure data correlatability is the use of sensor simulation. We propose that sensor simulation techniques can be used to model the sensor response for a range of sensor types for a given ore type. This can be achieved by developing uniform sample models which are representative of the ore type for which sensor fusion is being evaluated. These models can then be used, by each research group with expertise on a given sensor, to simulate the response of the sensor to the material. This can enable the simultaneous simulation of the sensor response to a given material in the same conditions for a wide range of sensor types, enabling correlated datasets to be produced. These datasets can be combined with any available experimental data to evaluate the sensor fusion potential for the material. The potential for using simulations to evaluate the suitability of a single sensor type for sorting a given ore was demonstrated in three papers identified in the review as discussed below.

In an investigation by Neubert and Wotruba [23] the potential use of XRT sensor-based sorting for rare earth element (REE) ore was evaluated using a combination of experiments and Monte Carlo simulations. Artificial samples containing the REE mineral bastnaesite with concentrations from 0.5%–5% and grain sizes from 125 to 1000 μm within a calcite or quartz matrix were prepared. A XRT sensor was used to measure the effect of the REE content and grain size on the X-ray transmission to evaluate the sorting potential of the technique. Additionally, a Monte Carlo simulation was used to model the transport and interactions of incident X-rays passing through a representation of the artificial samples. It was found via both experimental tests and Monte Carlo simulations that the transmission was reduced significantly as the REE grade was increased, indicating a strong sorting potential, as shown in Figure 2. As well as showing the suitability of the sorting technique for REE ores, the study also showed that the Monte Carlo simulations were able to model accurately the change in transmission with increased REE content. Note that while the trends were very similar, the simulation consistently predicted changes in transmission approximately twice that of the experimental tests. This difference was attributed by the authors to over simplified assumptions made in the design of the Monte Carlo model. Another potential aspect contributing to the difference is that the experimental measurements were compared directly with the simulated photon fluence. This did not take into account any effect from the photon detector used in the experiments.

In a study by Li et al. [37] a Finite Element Method simulation of an inductance-based sensor to measure the electrical impedance of ore was developed. The model was used to simulate the response of the sensing technique for copper and aluminum ores. First the simulations were validated against published experimental impedance measurements from an investigation by Tong et al. [36]. As shown in Figure 3, it was found that the simulations were able to reproduce effectively the response observed in experiments. This confirmed that the simulation was able to model effectively the sensor results. A simulation model of aluminum ore particles was developed. The model was able to generate particles with heterogeneous aluminum distributions reflecting the natural heterogeneity of the ore. The response to each modelled particle was simulated, producing a dataset of the sensor response to evaluate the potential of the sensor for sorting the ore. This dataset was used to train a neural network classification algorithm to sort the material into product and waste classes with particles containing more than 2% aluminum classified as product. It was found that for the evaluated material that the sensor data processed using the classification algorithm was able to sort product to product with an 82% efficiency and waste to waste with a 97% efficiency. This paper demonstrates that simulations can accurately reproduce experimental results and can be used to produce a dataset, with which sensor-based sorting can be evaluated.

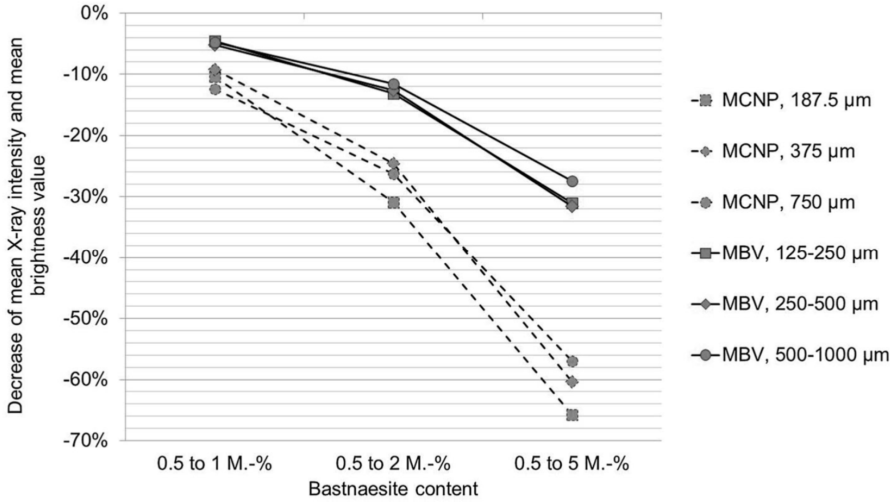

Figure 2. The relative decrease in X-ray transmission with higher bastnaesite concentrations relative to a 0.5% concentration. The results are shown for a range of bastnaesite grain sizes. The mean brightness value (MBV) and X-ray intensity are shown for the experimental tests and MCNP simulations respectively. Courtesy of Neubert and Wotruba [23].

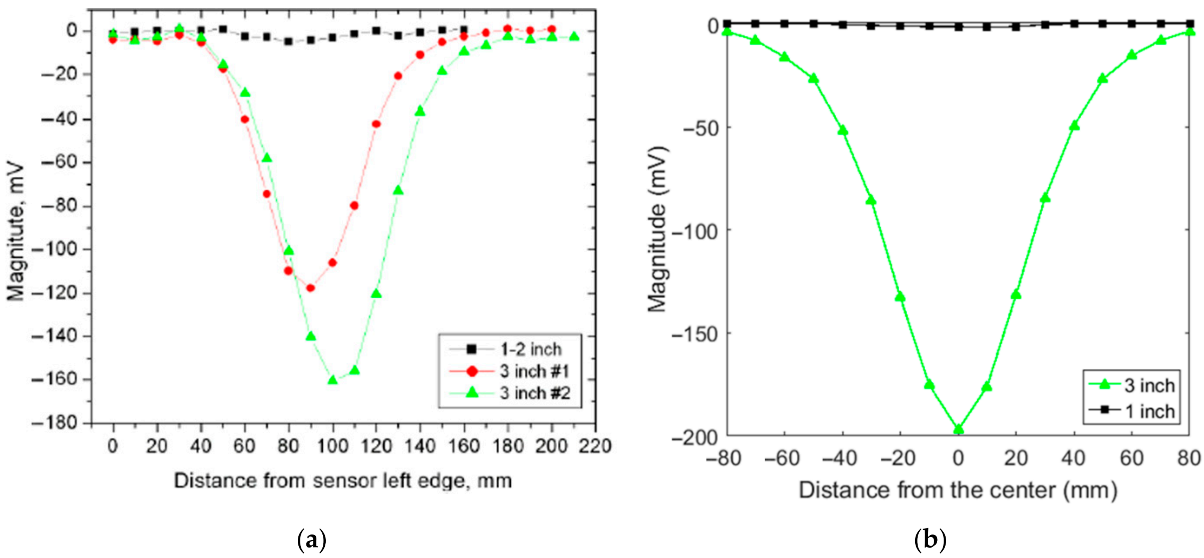

Figure 3. (**a**) Sensor response to chalcopyrite particles from experimental measurements; (**b**) Sensor response to chalcopyrite particles from simulations. Courtesy of Li et al. [37].

In a study by Duan et al. [40] finite-difference time-domain simulations were used to perform an initial evaluation of the use of microwave imaging to sense gold and silver inclusions within ore. Micro-CT scans of core samples combined with mineralogical mapping data were used to generate a model of the core samples within the simulation. The simulation showed that the highly conductive silver and gold particles resulted in a strong response even from small inclusions, indicating that the technique is a promising method for determining the presence of trace quantities of the precious metals. Future experimental tests are planned by the group to validate these simulation results. This paper demonstrates the potential of using off-line sensor data such as micro-CT and QEMSCAN data to produce an ore model for use in simulations to evaluate sensor response.

These simulation studies show that it is possible to model the response for a range of sensing techniques for a given material and that models could be used to predict sorting efficiency for a group of simulated ore particles [23,37,40]. Additionally, it was found that geological data from off-line sensing techniques can be used to build an ore particle model [40]. These findings suggest an approach to evaluate sensor techniques for sensor fusion would be to create a common model of ore for which sensing techniques are investigated using geological knowledge of the mined ore supplemented with off-line sample sensing such as micro-CT. This common model can then be used to simulate the response for a range of sensing techniques to provide data for analyzing the potential for sensor fusion. The use of a common model can be facilitated by using open-source simulation software capable of modelling a wide range of particle physics, such as Geant4 [44,45]. As many of the main sensing techniques such as XRF, XRT, fluorescence and PGNAA rely on particle physics interactions, their response can be modelled within the same software toolkit, helping to ensure comparability.

3.4.2. Data Synchronization

Once data is available for evaluation of sensor fusion techniques, it is important to ensure that the data is correlatable and comparable. This generally requires the synchronization of both the temporal and spatial sampling of the evaluated sensing techniques to ensure that data from the same sampled material is compared. Approaches to achieve data synchronization are proposed and discussed.

To ensure correlatability in test work studies, as discussed in the previous section, care must be taken to ensure that the same samples are presented to each evaluated sensor and any supplementary simulation data must use a sample model representative of the sampled material. For measurements from multiple sensors installed at a mining operation, the resulting data can only be correlated if the sensors are installed at the same point within the mining and mineral processing operation. For example, two sensors would have to be located on the same conveyor belt in order to be correlatable and preferably as close together as possible.

It is necessary to ensure that the sampling times are synchronized to ensure that the compared data is corresponding to measurements of the same material. For the sampling of material in motion on a conveyor belt the distance between the installed sensors and the velocity of the conveyed material must be accounted for to correct for the time delay between the same material being presented to each sensor. By comparing data measurements separated by this delay it is possible to compare the results from the sensors as the same material is being measured. An effective way to ensure that data from multiple sensors correspond to measurements of the same material is to co-locate several sensor types within a single sensing unit. Sensor units with multiple sensor types were used in several of the discussed studies, however the potential for sensor fusion was not evaluated [17,22,31]. To correct for varying sensor sampling times to ensure that the same material is sampled data from a sensor with a shorter sampling time can be integrated to match the sampling time of the slower sampling sensor. Although this can enable comparison of the sensor results, it is at the cost of the higher time resolution of the faster sampling sensor.

It is also necessary to synchronize the spatial sampling of the material to ensure that measurements are comparable. It is easier to compare sensor results with the same spatial sampling profiles, however, in some cases techniques can be used to compare sensors with different spatial sampling types. It is possible to compare results from bulk sampling and surface sampling sensors for relatively homogenous ore types where the sampling distribution has a reduced effect on the observed values [10]. It is also possible to compare data from spot sensors and surface sensors provided sufficient and representative spot sample measurements are taken to ensure results represent the surface of the sensed material [12,34]. Different sensor types can also provide data in different spatial formats, e.g., image and point data. It is possible to integrate data with a higher spatial resolution to compare with lower spatial resolution data. However, like the case with temporal integration this is at the expense of spatial resolution in the measured data. Another technique for comparing image and point data is to take a weighted combination of features extracted from the image [34]. For different sensor fields of view, it can be possible to restrict a sensor which is capable of sampling a wide field of view to match the narrower field of view of the sensor it is being fused with. While this enables direct comparison it is at the expense of the capability to sample a wider distribution of the ore.

3.4.3. Data Analytics

With the availability of synchronized and correlatable multi-sensor data, it would be possible to evaluate the potential for sensor fusion. There are two main approaches to evaluating the sensor fusion potential, via expert knowledge of the fundamental characteristics of each sensing technique and via the use of machine learning techniques.

The information on the sensing techniques from the literature review can be used to evaluate potential sensor-fusion pairings based on the fundamental mechanisms of the considered sensing techniques and the sampling profiles. Ideal sensor pairings would provide complimentary information, have similar sampling profiles and have a good response to the considered ore type. Examples of potential sensor fusion combinations identified using knowledge of the sensing techniques that were previously discussed include the combination of PGNAA/XRF elemental data with hyperspectral imaging, using fluorine fluorescence sensors to augment PGNAA sensor data and using LIDAR data to aid extracting material density and atomic number from XRT data. Evaluating potential data fusion applications based on knowledge of the sensing techniques requires the collaboration of several research groups with expertise covering the sensors and their fundamental mechanisms. With synchronized and correlatable data and the knowledge of the sensing techniques from the research groups, it would be possible to identify potential beneficial sensor combinations based on the ore characteristics and the sensor capabilities.

There are likely to be beneficial sensor combinations that are not readily apparent from the characteristics of the sensors. For these cases, a data driven approach could be used to evaluate such beneficial combinations using machine learning techniques. Collaboration with a research group with expertise in machine learning techniques would be beneficial to help identify the best ways for combining and analyzing the distinct data sets from multiple sensor types. An example of analyzing combined datasets from separate sensors and using classification algorithms to sort ore particles is presented by Desta and Buxton [34]. An advantage of some machine learning techniques, such as deep learning, is the ability to process a large heterogeneous data superset consisting of the results from multiple distinct sensor types. This can enable the processing of data from a broad range of sensor types to determine whether their combination can improve ore classification.

As previously discussed, it is important to consider the uncertainty within the sensor measurements used in sensor fusion and the resulting potential for misclassification when using the fused data set for control decisions. For sensor fusion applications where expert knowledge is used to combine sensor results, the method for combining the data is known and therefore traditional uncertainty propagation techniques can be used to determine the uncertainty of the fused result. It is more difficult to determine the uncertainty for sensor fusion performed via a machine learning technique such as deep learning algorithms, as the dependence of the fused result on the input data sources is often complex. For these cases, traditional uncertainty propagation techniques are not feasible, however new techniques to evaluate the combined uncertainty are being developed. One example is the determination of uncertainty for deep learning techniques using Bayesian dropout as discussed by Gal and Ghahramani [46].

4. Conclusions

Numerous studies and reports of sensor-based sorting in mineral processing using a wide range of sensing techniques including XRT, optical/infrared imaging, XRF and PGNAA were identified and discussed in this review. It was found that for all the identified papers at least one of the sensing techniques evaluated was capable of effectively sorting the investigated material, showing the potential benefits from implementing sensor-based sorting. The basis of each of the major sensing technologies and the resulting measured characteristics and sampling was discussed. This information can aid selection of sensing technique, based on geological information, to ensure the selected method has a reasonable potential to differentiate ore and waste and provides sufficient sampling to provide representative data for the considered sorting technique. The large number of recent publications demonstrates a significant interest in implementing sensor-based sorting techniques to upgrade ore grades while reducing the processing of waste rock. This increase is driven by the current conditions of declining ore grades and a significant demand for resources resulting in a need for the efficient processing of low-grade ores [4].

The growing uptake of sensor-based sorting techniques in mining increases the likelihood that a mining operation will install two or more sensor types. This offers the potential to combine data from multiple sensor types to improve the characterization of sensed ore and hence improve sorting efficiency and processing control. A classification of sensor-fusion applications in mineral processing was proposed. A few implementations of sensor fusion [19,27,34] were found in the literature and were discussed along with several identified potential applications. It was found that while sensor fusion offers significant potential, few implementations have been reported, and these typically have some limitations. The reported cases generally consist of a relatively low level of data fusion, or when a high degree of fusion was performed it was done for two similar sensing systems, reducing the new information that could be extracted. When considering potential combinations of sensing techniques for sensor-fusion it was determined that ideally the fused techniques should provide distinct types of information on the sensed material to maximize the information available for sorting. Additionally, the sensing techniques should have as similar sampling profiles as possible to minimize complications arising from comparing the sensor data.

It was determined that a major factor limiting implementation of sensor fusion is the poor availability of correlatable datasets of the sensor response from multiple sensor types for the same material sample. This was found to result from most research groups specializing in a single sensor type, generally leading to each sensor being considered and installed in isolation. A program involving multiple research groups collaborating to evaluate the response of multiple sensor types for a particular ore is a requirement to ensure effective evaluation of sensor fusion potential. A complication for lab testing is the logistical issues involved with shipping a large sample to many groups and ensuring the sample is in the same configuration. A potential solution proposed is the use of simulations of sensor response for a standardized ore model to supplement experimental results. Another potential solution for providing correlatable data is the use of sensor systems providing multiple sensing techniques in the same installed device. The co-location of the sensing techniques helps ensure data correlatability. With available data, the potential for sensor fusion can be evaluated using traditional techniques relying on expert knowledge of the fundamental sensing mechanisms of each technique or via a machine learning approach.

The use of sensor-based sorting enables efficient processing of lower ore grades, reducing fine waste production and energy and reagent consumption. With greater sensor use, fusing multiple sensor types offers the potential to improve significantly ore classification and sorting efficiency. However, significant work on acquiring correlatable data and developing sensor fusion techniques will be required to realize this potential.

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