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A review on automated sorting of source-separated municipal solid waste for recycling

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ABSTRACT

A crucial prerequisite for recycling forming an integral part of municipal solid waste (MSW) management is sorting of useful materials from source-separated MSW. Researchers have been exploring automated sorting techniques to improve the overall efficiency of recycling process. This paper reviews recent advances in physical processes, sensors, and actuators used as well as control and autonomy related issues in the area of automated sorting and recycling of source-separated MSW. We believe that this paper will provide a comprehensive overview of the state of the art and will help future system designers in the area. In this paper, we also present research challenges in the field of automated waste sorting and recycling.

Contents

Abbreviations: ABS, acrylonitrile butadiene styrene; ACQ, alkaline copper quat; ADC, analog digital converter; Al, aluminum; As, arsenic; Au, aurum (gold); CCA, chromate copper arsenate; CCD, charge coupled devices; CBR, case-based reasoning; C&D, construction and demolition; C/H, carbon and hydrogen; CMOS, complementary metal oxide semiconductor; Cr, chromium; Cu, copper; DAQ, data acquisition; DE-XRT, dual energy X-ray transmission; DNA, deoxyribonucleic acid; EDXRF, energy dispersive X-ray fluorescence; EMS, electromagnetic sensor; FUSSER, fuzzy spectral and spatial classifier; GDP, gross domestic product; HDPE, high-density polyethylene; HIPS, high impact polystyrene; HIS, hue saturation and intensity; HSI, hyperspectral imaging; ICA, independent component analysis; KNN, k-nearest neighbor; LDPE, low-density polyethylene; LED, light-emitting diode; LIBS, laser induced breakdown spectroscopy; LIPS, laser induced plasma spectroscopy; MDS, magnetic density separation; Mg, magnesium; MIR, midrange infrared; MSW, municipal solid waste; Nd:YAG, neodymium-doped yttrium aluminum garnet; NdFeB, neodymium magnets; NF, non-ferrous; Ni, nickel; NIR, near infrared; OCC, old corrugated cardboard; ONP, old news paper; Pb, lead; PC, polycarbonate; PCA, principal component analysis; PE, polyethylene; PET, poly(ethylene terephthalate); PLA, polylactide; PPP, purchasing power parity; PP, polypropylene; PS, polystyrene; PSW, plastic solid waste; PVC, poly(vinyl chloride); PU, processing unit; SS, stainless steel; SVS, smart vision system; RGB, red green blue; Rx, receiver; Tx, transmitter; UNEP, united nations environment programme; UV, ultraviolet; VIS, visual image spectroscopy; WP, white paper; XRF, X-ray fluorescence; XRT, X-ray transmission; Zn, zinc; 3D, three-dimensional.

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1. Introduction

Rapid urbanization and industrialization is causing an unprecedented rise in the generation of municipal solid waste (MSW) worldwide (Chiemchaisri et al., 2007; Liu and Wu, 2010; Saeed et al., 2009). Countries with a relatively higher GDP tend to produce a larger quantity of MSW (see Fig. 1(a)). Projections show that the generation of MSW across major metropolitan cities worldwide will rise from 1.3 billion tonnes in 2012 to 2.2 billion tonnes in 2025 (Hoornweg and Bhada-Tata, 2012; Kawai and Tasaki, 2016). MSW is often a rich source of various useful recyclable materials such as metal, paper, plastic, and glass (see Fig. 1(b)). Effective MSW management can enable recovery of valuable recyclable materials and reduction of negative environmental impact. Waste sorting is a key step in MSW management for the recycling of materials. Researchers worldwide have been actively exploring automated sorting techniques for efficiently processing increasing quantities of MSW. This paper summarizes developments that have taken place in the last decade in the area of automated sorting and recycling of source-separated MSW.

At the waste collection stage, source segregation is often performed for a preliminary sorting of recyclables. The practice of source segregation may not be followed uniformly at all the locations and the extent of required sorting may vary. Developing countries seldom practice source segregation. In this review, we assume that the practice of source segregation is performed and thus the input to the automated waste sorting process is source-separated MSW.

Following some early patents filed by Holloway (1989) and Roman (1992), many other automated solid waste sorting techniques have been reported by archival journals and technical conferences. Several review articles have been reported frequently in areas related to automated/semi-automated waste sorting for recycling and are as follows:

- Dodbiba and Fujita (2004) surveyed various sorting techniques for separating plastic materials. The review primarily focused on non-sensor based design, development, and testing of wet and dry based separating/sorting techniques.
- Shapiro and Galperin (2005) reviewed various air classification techniques for solid particles.
- Al-Salem et al. (2009) reviewed chemical recycling and energy recovery from plastic solid waste (PSW).
- Sadat-Shojai and Bakhshandeh (2011) reviewed energy recovery, mechanical and chemical recycling and separation methods by recycling Poly(vinyl chloride) (PVC) waste.
- Gaustad et al. (2012) surveyed physical and chemical separation methods in sorting and removal of impurities from aluminum debris.
- Wu et al. (2013) reviewed triboelectrostatic separation techniques for sorting plastic from waste.
- Rahman et al. (2014) reviewed sorting techniques to segregate waste paper and also recommended low cost sorting techniques corresponding to the paper type present in the waste.
- Cimpan et al. (2015) reviewed physical processing of waste to segregate recyclables from MSW. The review mainly focused on case studies of operational experience without emphasizing many aspects of automation including material handling, sensors and control.
- Wang et al. (2015) published a comprehensive review on flotation separation of various types of plastics from waste.

This paper provides a comprehensive overview of the state of the art in the field of automated sorting of source-separated MSW for the purpose of recycling. This paper is intended to help designers of automated waste sorting systems select suitable technologies such as sensors, actuators, control algorithms, and sorting processes for recycling source-separated MSW. This review presents a detailed discussion on various comminution and sorting techniques used for segregating recyclable materials. The paper also presents a detailed discussion on the variety of materials that can be sorted as well as the sensors and material handling systems used. In addition, classification rates obtained by various sorting techniques reported in the literature in the last decade are detailed. A detailed discussion on the levels of automation implemented in the waste sorting systems is presented. This review also identifies open research issues and suggests future research directions in the field of automated waste sorting.

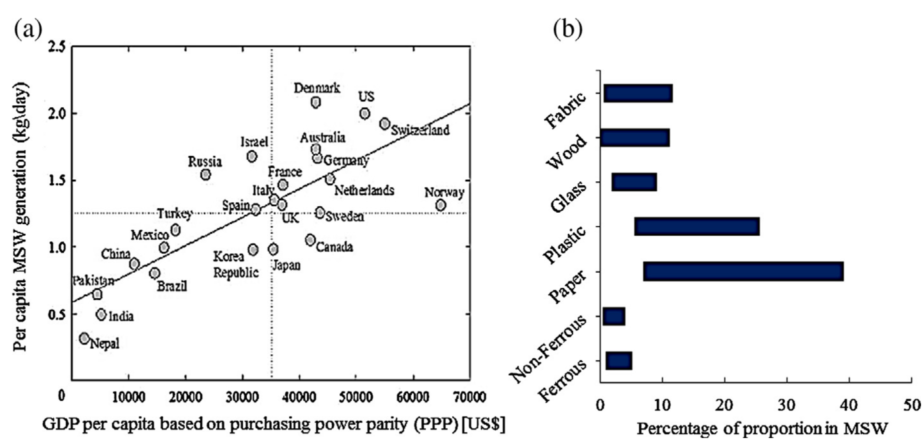

Fig. 1. (a) Per capita MSW generation versus GDP per capita based on purchasing power parity. (b) Proportion of recyclables in MSW. *Source:* ADB (2013), Annepu (2012), Badgie et al. (2012), Banar et al. (2009), Burnley (2007), Damanhuri et al. (2014), Edjabou et al. (2015), EOCSSB (2012), EPA (2014), Hoornweg and Bhada-Tata (2012), Khatib (2011), Masood et al. (2014), MfE (2009), Montejo et al. (2011), OECD (2012), Randell et al. (2014), Sharma and McBean (2007), and UNEP (2012).

A large number of research papers are reported in the area of automated source-separated MSW sorting and thus it is very difficult to include all of them in this paper due to space constraints. We have thus categorized and organized the literature based upon comminution process, direct sorting, and indirect sorting. The scope of this review paper is listed below.

- The main focus of this paper is to survey the state of the art automated sorting techniques for recovering various recyclable waste fractions like metal, plastic, paper, glass and wood from source-separated MSW. However, some of the techniques discussed in this paper may also be applicable to other waste streams such as industrial waste, electronic waste, and construction and demolition waste. Henceforth, we refer to 'source-separated MSW' as 'MSW' for the sake of brevity.
- This paper mainly surveys journal and conference publications during the period 2004–2015.
- This paper compares the sorting techniques reported in the literature in terms of diversity of materials sorted, accuracy of sorting, speed of operation, robustness, flexibility, and reliability.

2. Automated sorting techniques for various MSW fractions

Automated waste sorting techniques can be categorized into two types: direct sorting and indirect sorting. Direct sorting techniques utilize material properties like magnetic susceptibility, electrical conductivity and density for heavy media separation by applying external fields like magnetic, eddy current and gravity respectively (Gaustad et al., 2012; Mesina et al., 2003; Svoboda, 2004). Indirect sorting, on the other hand, employs sensors to detect the presence and often the location of recyclables in the waste so that automated machines or robots can be employed to sort the detected recyclable materials.

Table 1 lists various sorting techniques and their applicability to different types of recyclable materials such as metals (ferrous and non-ferrous), plastic, paper, glass, wood and organic waste. Direct sorting techniques are discussed in details in Section 2.2 while indirect sorting techniques in Sections 2.3.1–2.3.5.

Fig. 2 illustrates the entire process flow of automated sorting of recyclable materials from MSW. Initially, pre-treatment is performed using screw press, disc screen, and shredder + magnetic techniques. After this, dry waste is obtained and later dry waste fraction is subjected to comminution or shredding processes that include swing-hammer shredder, rotating drum, alligator shears, hammer mill, ring mill, shear shredder and impact crusher based techniques. In order to sort ferrous materials, magnetic drum techniques are used. After this, non-ferrous metals are sorted using various indirect sorting techniques like eddy current, LIBS, DE-XRT and optical sort and hyperspectral sort.

2.1. Comminution techniques

Bulk waste material is pulverized into particles of uniform size using forces produced by pressure, impact, cutting or abrasion during comminution, for convenient handling and to remove contaminants (Bonifazi and Serranti, 2012; Buchan and Yarar, 1995; Kasper et al., 2015). Some commonly used tools for comminution of MSW are swing hammer shredders, rotating drums, alligator shears, hammer mills, ring mills, shear shredders, and impact crusher.

2.2. Direct sorting

This section presents various direct sorting techniques used for MSW.

Table 1
Various sorting techniques based upon composition of waste.

	Sorting technique																	
	Direct sorting (see Section 2.2 [a–m])													Indirect sorting (see Sections 2.3.1–2.3.5)				
	Screw-press (a)	Disc-screen (b)	Shredder + Magnet (c)	Magnetic drum (d)	Magnetic head pulley (e)	Magnetic Overhead belt (f)	Eddy current (g)	Magnetic density separation (h)	Triboelectrostatic (i)	Hydrocyclone (j)	Jigging (k)	Froth flotation (l)	Air separator (m)	Eddy current (2.3.1)	LIBS (2.3.2)	X-ray sort (2.3.3)	Optical sort (2.3.4)	Spectral sort (Section .5)
Material Organic waste	✓	✓	✓															
Ferrous metal			✓	✓	✓	✓					✓							
Non-ferrous metal							✓	✓	✓		✓			✓	✓	✓	✓	✓
Plastic								✓	✓	✓	✓	✓	✓		✓	✓		✓
Paper													✓				✓	
Glass																	✓	✓
Wood															✓	✓		

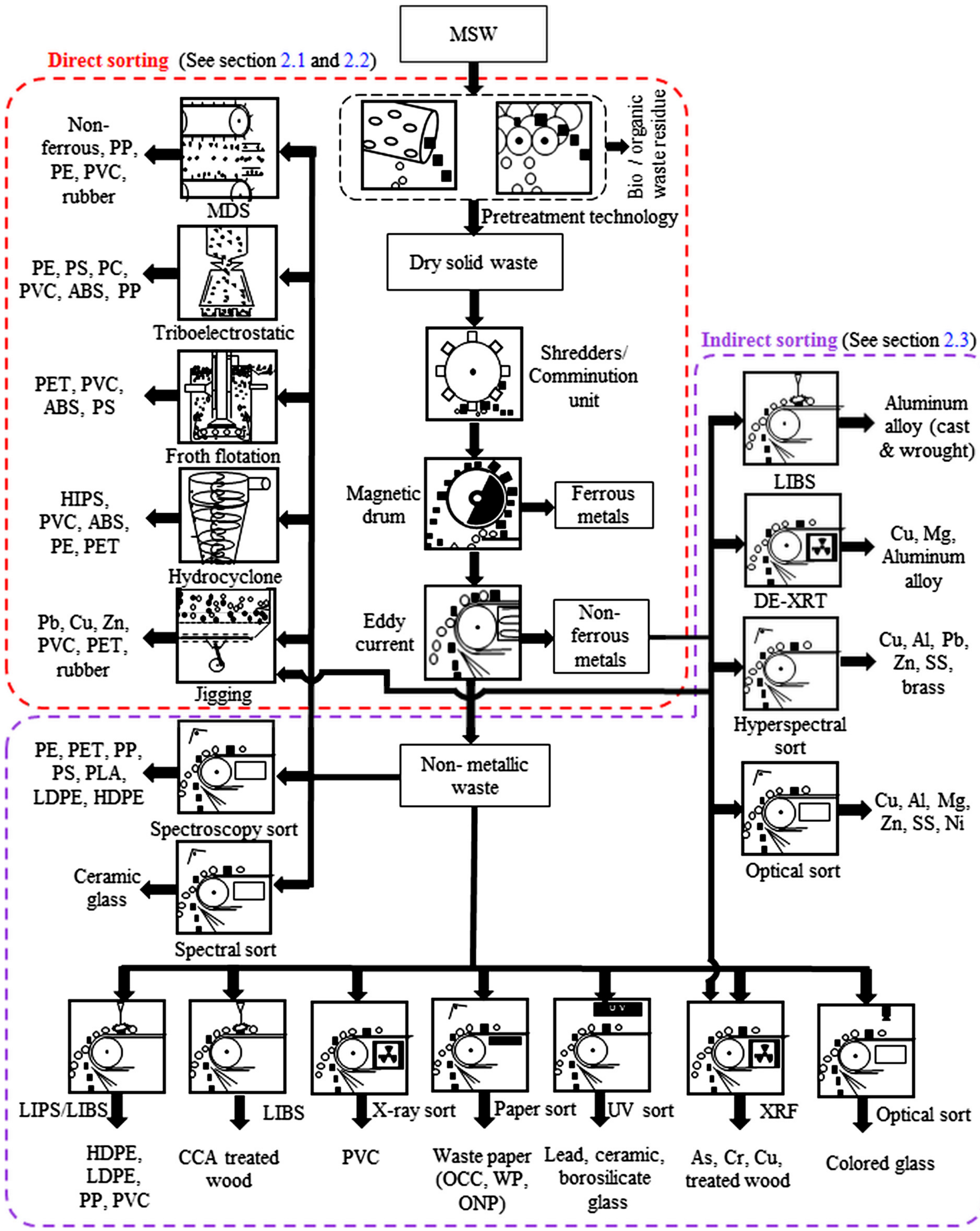

Fig. 2. Flow diagram of automated sorting of recyclables from MSW. First, MSW is processed via pre-treatment (sorting organics from dry waste fraction) techniques. Then the dry waste fraction is subjected to comminution and shredding processes. This is followed by sorting metallic waste fraction from non-metallic waste fraction. After this, non-metallic waste fraction is sorted into its various constituents.

(a) ***Screw press:*** In the screw press pre-treatment technique (shown in Fig. 3(a)), the organic waste fractions are squeezed through narrow slits resulting in segregation of soft and wet fractions from plastic, paper, wood, animal bone and metal (Hansen et al., 2007; Jank et al., 2015).

(b) ***Disc screen:*** In this technique, the rotating discs are equally spaced in a chamber (see Fig. 3(b)), where the small and heavy organic waste fractions fall between the discs, while the light and large fractions are transported towards the edge of the disc (Hansen et al., 2007; Jank et al., 2015).

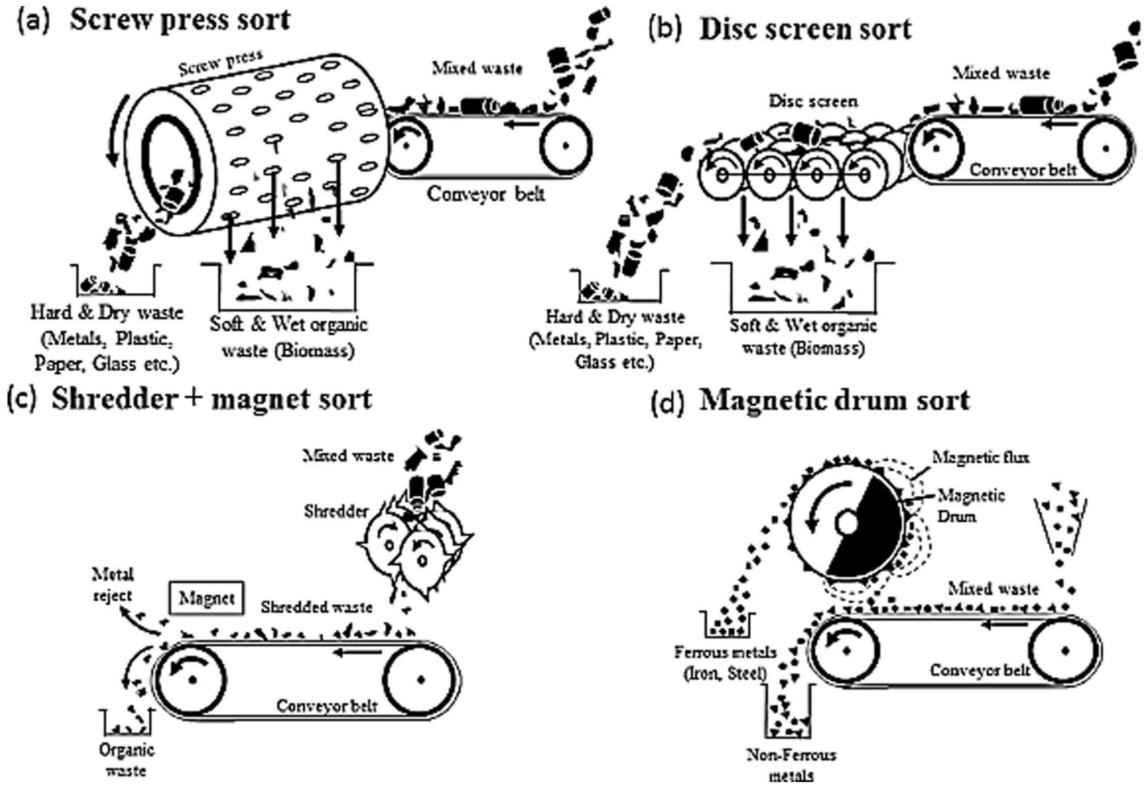

Fig. 3. Various direct sorting techniques for pre-treatment of MSW. (a) Screw press sorting technique. (b) Disc screen sorting technique. (c) Shredder + magnetic sorting technique. (d) Magnetic drum sorting technique.

(c) ***Shredder along with magnet:*** The combination of shredder and magnet is utilized for sorting paper and organic matter from MSW stream (see in Fig. 3(c)) (Hansen et al., 2007). The input stream of this technique must be free from plastic contaminants. With this technique the recovery rate of bio-waste was approximately 98% free from metal contaminants (Hansen et al., 2007).

(d) ***Magnetic drum:*** The magnetic drum technique segregates ferrous fractions from non-ferrous and other mixed waste fractions by measuring the magnetic susceptibility of waste (Kelland et al., 1974; Svoboda and Fujita, 2003). The magnetic drum consists of a stationary permanent magnetic assembly placed on one half of its circumference as shown in Fig. 3(d). As the mixed waste is supplied, the powerful magnetic flux attracts and holds the ferromagnetic material to the revolving shell. The revolving shell carries the ferrous fractions to the far edge of the drum and collects them into respective bins (see Fig. 3(d)) (Oberteuffer, 1973; Ohara et al., 2001; Svoboda, 2004). Magnetic drum based techniques are incapable of distinguishing between various non-ferrous metal fractions.

(e) ***Magnetic head pulley:*** The magnetic head pulley technique segregates ferrous waste fractions from non-ferrous. The mixed waste is transported through a material handling system (conveyor belt) near to a magnetic head pulley. Ferromagnetic waste fractions are held by the magnetic belt while other non-ferromagnetic fractions are discharged (see Fig. 4(e)) (Bonifazi and Serranti, 2012).

(f) ***Magnetic overhead/cross belt:*** The magnetic overhead/cross belt technique segregates ferrous waste fractions from mixed waste stream. The magnetic overhead belt has a magnetic field acting normal to the direction of mixed waste flow (shown in Fig. 4(f)). Thus, the metal pieces are attracted and removed from mixed waste. The metal pieces are subsequently discharged to a collection bin via a moving belt (Bonifazi and Serranti, 2012).

(g) ***Eddy current:*** The segregation is performed using a rotary drum type separator. The rotary drum is in-line with Neodymium magnets (NdFeB) with alternating North and South poles as shown in Fig. 4(g). A thin layer of a mixture of non-ferrous metal fractions (ferrous fractions are separated beforehand using other techniques) and non-metallic waste is transported towards the rotary drum using a conveyor system (Bonifazi and Serranti, 2012; Gaustad et al., 2012; Krivtsova et al., 2009; Rem et al., 1998). The external magnetic flux repels the non-magnetic electrically conductive metal fractions from the mixed metal waste. This technique has a low operating cost and yields a high degree of purity of recovered metal. This technique however is not designed for sorting metals that may become hot in an eddy current field as that may lead to damage of the separator.

(h) ***Magnetic density separation (MDS):*** The MDS technique utilizes magnetic liquid (ferrofluid) as the separation medium. Waste input is mixed with the magnetic liquid and introduced into a separation zone as shown in Fig. 4(h). Large magnets are used for creating a magnetic field. The magnetic field reduces exponentially with the distance from the magnet. Due to the magnetic field, the effective density of the magnetic fluid gets altered (Bakker et al., 2009; Hu, 2014; Luciani et al., 2015; Muchova et al., 2009; Rem et al., 2012). By varying the density of the magnetic fluid present in the waste input, the constituent recyclable polymeric materials of different densities can be made to float at different levels (Hu, 2014; Luciani et al., 2015). The floating polymeric materials are then collected via separator blades (see right side of Fig. 4(h)).

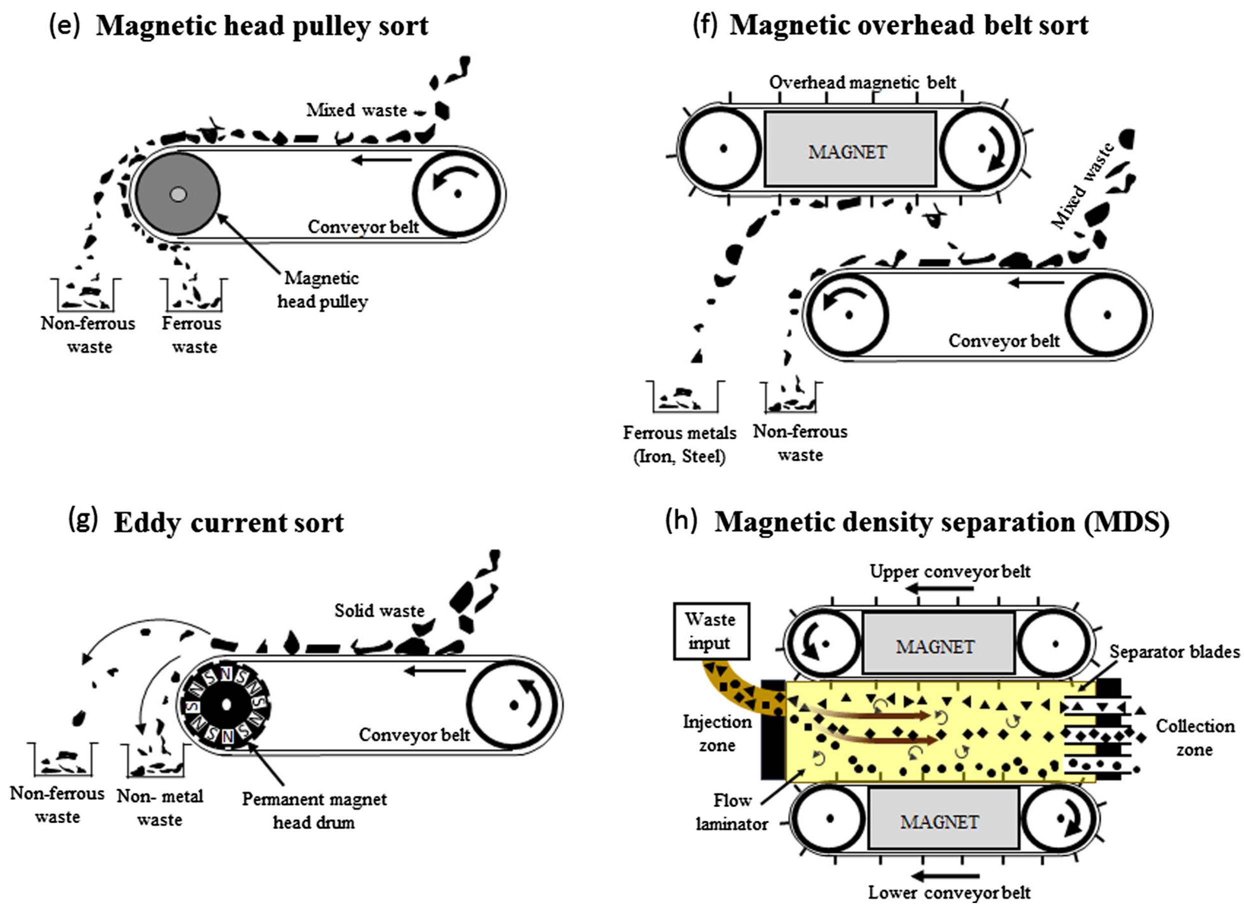

Fig. 4. Various direct sorting techniques for pre-treatment of MSW. (e) Magnetic head pulley sorting technique. (f) Magnetic overhead belt sorting technique. (g) Eddy current sorting technique. (h) Magnetic density separation.

(i) ***Triboelectrostatic separation:*** Triboelectrostatic separation process is used for sorting plastics. The physical phenomenon used for sorting is 'contact electrification' or 'frictional electrification' (Lowell and Rose-Innes, 1980). When mixed waste is passed through a tribocharging chamber, shredded plastic present in the waste gets charged with different polarities by friction electrification (see Fig. 5(i)). The charged pieces of the mixed waste are then passed through an electric field to separate them. The trajectory of each piece of waste is determined by the amount of charge carried. The electric field is so designed that the pieces of shredded plastic materials fall into respective bins (Li et al., 2015; Wu et al., 2013).

(j) ***Hydrocyclone:*** Hydrocyclone utilizes centrifugal force for density separation (see Fig. 5(j)). The technique can be used for the separation of materials like ABS (Acrylonitrile butadiene styrene), PE (Polyethylene), HIPS (High impact polystyrene), and PVC (Poly (vinyl chloride)). Various factors influencing the liquid separation of a given material are its variation in density (from fillers, pigments, porosity, etc.), wettability, shape factors of size-reduced particles and level of liberation from other materials (Al-Salem et al., 2009; Richard et al., 2011; Yuan et al., 2015).

(k) ***Jigging:*** Jigging is a gravity concentration technique for sorting, which works based on the interaction of buoyancy, drag, gravity, and acceleration. In this process the solid-water mixture is placed into a perforated vessel called a pulsatile bed (de Jong and Dalmijn, 1997). In a wet jig bed, the bed is shaken ("jigged") to induce vertical currents in the water column, which lifts the solid particles (see Fig. 5(k)). The currents can be of two types: ascending current and descending current (Pita and Castilho, 2016). Materials with higher density get settled at the bottom. Segregation is performed according to the material density, size, and shape. The main parameters that affect the jigging process are: jig stroke length, initial bed height and jigging speed (Cazacliu et al., 2014; de Jong and Dalmijn, 1997; Li et al., 2007; Pita and Castilho, 2016).

(l) ***Froth flotation:*** The froth flotation technique utilizes the hydrophobicity of plastic to separate it from the waste stream. Before processing, the waste is shredded into fine particles or pulp using a comminution process (Fraunholcz, 2004; Wang et al., 2015) and mixed with water. A schematic diagram of froth flotation is depicted in Fig. 5(l). In this process, air is dissolved in the mixture of water and the waste pulp under high pressure. The dissolved air is then released into a flotation section at atmospheric pressure. This leads to the formation of froth on the surface of water-waste mixture. The suspended plastic particles, due to their hydrophobicity, get attached to the bubbles in the froth thus formed. The combined specific gravity of the bubbles carrying plastic particles is less compared to the fluid medium resulting in flotation. This flotation is used for separating plastic from the water-waste mixture (Patachia et al., 2011; Takoungsakdakun and Pongstabodee, 2007; Vajna et al., 2010; Wang et al., 2012, 2014).

(m) ***Air separator:*** A compressed air nozzle is used for preliminary recovery of light non-metallic fractions (e.g., polymers, paper, foam, rubber, fibers, etc.) from previous processes, like magnetic sorting and eddy current type separation

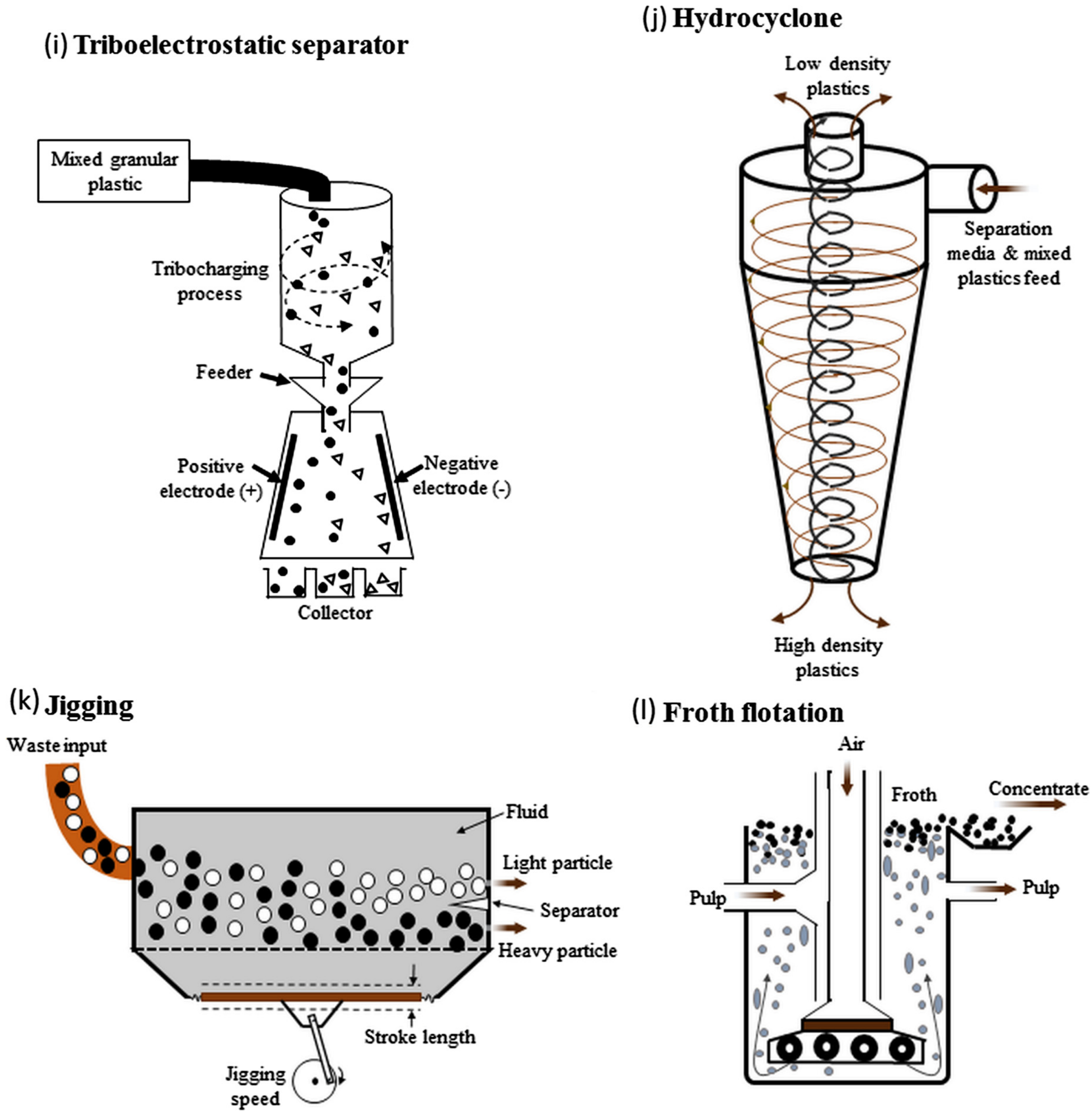

Fig. 5. Various direct sorting techniques for pre-treatment of MSW. (i) Triboelectrostatic separator. (j) Hydrocyclone based sorting. (k) Jigging based sorting. (l) Froth flotation based sorting.

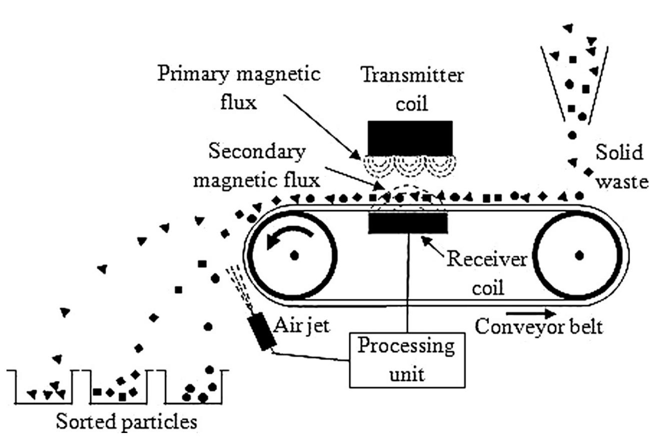

Fig. 6. Eddy current based sorting technique consisting of sensor unit for detection of NF metals and processing unit for ejection of various MSW waste fractions.

(Bonifazi and Serranti, 2012). A compressed air nozzle is used to release high pressure air jet to impart a force of separation on the mixed waste sample. Lighter particles get blown away to a larger distance while the heavier ones to a shorter distance. Separation is thus performed by keeping separate bins at various distances from the air nozzle for collecting the particles of differing weights.

2.3. Indirect sorting

Sensors are used for detecting recyclable materials in the bulk input waste followed by segregation using various actuators in indirect sorting.

2.3.1. Eddy current based sorting

Electromagnetic sensor (EMS) is utilized for detection of non-ferrous metal fractions based upon electrical conductivity of the sample in eddy current based sorting (Braam et al., 1988;

Brojboiu et al., 2013; Mesina et al., 2003; Rahman and Bakker, 2012; Schlömann, 1975). When a magnetic flux generated by an electromagnetic coil is passed through a conductive test material then an eddy current is induced (Brojboiu et al., 2013; Mesina et al., 2003; Rahman and Bakker, 2012). Fig. 6 depicts the process of eddy current based sorting technique. A transmitter coil is suspended over the conveyor system and a receiver coil is fixed beneath the belt. An alternating current is supplied to the transmitter coil. A primary magnetic flux is produced in the axial direction of the transmitter coil. As the test materials are passed on a conveyor belt underneath the transmitter coil, an eddy current flows into the test material. According to the Lenz's law, the generated eddy current opposes the secondary magnetic flux as shown in Fig. 6 (Mesina et al., 2003; Rahman and Bakker, 2012). By measuring the secondary flux, the presence of ferrous metals in bulk waste is detected. Compressed air jet is then used for segregating the detected ferrous materials into their respective bins (see Section 2.2.(m)). The parameters that affect the process of eddy current based sorting include electrical conductivity and magnetic permeability (Kutila et al., 2005; Mesina et al., 2003).

2.3.2. Laser Induced Breakdown Spectroscopy (LIBS)

Laser Induced Breakdown Spectroscopy (Noll et al., 2001, 2008) utilizes a high power laser pulse. Los Alamos National Laboratory in collaboration with Metallgesellschaft were the pioneering group that developed the LIBS system in 1990 for the identification of metallic waste (Sattler, 1990; Sattler and Yoshida, 1993). LIBS provides high dimensional spectrometric information for the analysis of metal alloys (Grzegorzek et al., 2011), plastics (Gondal et al., 2007) and treated wood waste (Solo-Gabriele et al., 2004).

A LIBS system is composed of a solid state (Nd:YAG) Neodymium-doped yttrium aluminum garnet laser, a CCD spectral range spectrometer and a processing unit for fast data analysis (see Fig. 7). First, the bulk waste is brought into the inspection area, where the laser is focused over it. This leads to ablation of waste material, which generates plasma plumes (see Fig. 7). The radiation emitted from the ablated portion is captured by the CCD spectrometer. The optical spectroscopy reads and distinguishes the characteristic atomic emission lines and enables a quick analysis of the bulk waste followed by the detection of constituent materials. Next the mechanical system sorts the detected constituent materials into their respective bins.

An advantage of LIBS is that the segregation of waste takes place at a relatively higher volume and speed compared to the eddy current technique. A limitation of LIBS is that the waste sample must be free from lubricants, paints, or oxide layers (Gesing and Harbeck, 2008). In practice, this may be difficult to ensure.

Metal: Grzegorzek et al. (2011) developed a system in which a LIBS system is mounted over the conveyor system for acquiring material data. It had a camera and a line laser for sensing metals. Machine learning algorithms such as Naive Bayes (NB), support vector machines (SVM), and nearest-neighbor (NN) were used to classify materials based on their characteristics spectral emission signatures. SVM reportedly provided an accuracy of about 71% (Grzegorzek et al., 2011). A multivariate analysis technique is also used to estimate the elemental composition of test material and to classify (Gurell et al., 2012a,b).

Plastic: The recovery of plastic waste can also be performed by LIBS. When applied to plastics, it is sometimes called LIPS (Laser Induced Plasma Spectroscopy) instead (Sattler, 1990; Sattler and Yoshida, 1993). Gondal et al. (2007) proposed a LIBS based system which can identify various plastics like High Density Polyethylene (HDPE), Low Density Polyethylene (LPDE), Poly-propylenes (PP), Polystyrene (PS), Poly(ethylene terephthalate) (PET) and Poly(vinyl chloride) (PVC) on the basis of their carbon and hydrogen (C/H) line intensity ratio. Anzano et al. (2006) and Gornushkin et al. (2000) proposed a compact and reliable method for instant classification of different types of plastic particles by utilizing statistical analysis such as linear and rank correlations with LIPS. The spectra from the plastics are collected and monitored in the 200–800 nm spectral window and compared with reference libraries. These libraries are built using the spectral data from different groups of recycled plastic samples. Anzano et al. (2008) developed a system which overcomes the limitations in the previous method (Anzano et al., 2006), wherein the laser radiation atomizes the molecular particles of plastic when exposed. The classification is performed by utilizing instant ratio analysis of molecular bands for identification of different energetic materials (Anzano et al., 2008).

Wood: The wood waste quality is categorized into three types, namely, (i) 'A' type untreated wood such as wooden pellets, (ii) 'B' type painted or glued wood with nails such as frames, doors, and chipboards, and (iii) 'C' type treated with hazardous wood preservatives such as construction and demolition (C&D) wood waste. Isolating treated wood waste from untreated wood waste is a major concern, as it can contaminate the untreated wood

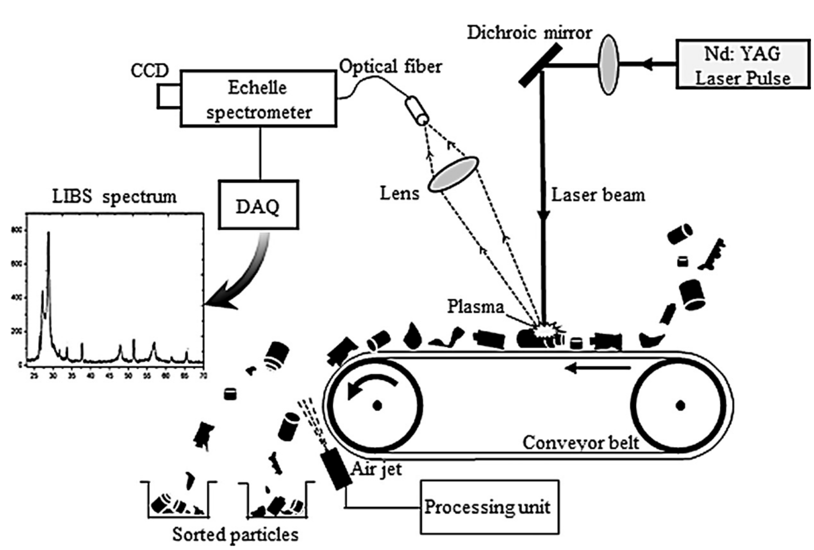

Fig. 7. Schematic setup for LIBS based sorting technique. Nd:YAG laser pulses induce plasma at waste pieces on the conveyor belt. Plasma radiation is detected in backward direction using fiber optics and grating spectrometer with a CCD detector and fast read-out electronics.

waste. Treated C type wood waste hosts a lot of preservatives like oil-borne preservatives, organic solvents and chromate copper arsenate (CCA) (Jacobi et al., 2007; Solo-Gabriele et al., 2004).

Several techniques have been proposed to sort CCA treated wood from the other wood waste types (Aono et al., 2012; Fellin et al., 2014; Hasan et al., 2011a,b; Jacobi et al., 2007; Solo-Gabriele et al., 2004). Aono et al. (2012) proposed the identification of CCA-treated wood by using a laser to form and analyze the plasma. Uhl et al. (2001) reported analysis of treated wood by LIBS and concluded that LIBS has the capacity to distinguish heavy metals in wood.

The LIBS technique utilizes an Nd:YAG laser emitter as seen in Fig. 7. The pulse emitted from the laser is focused onto the wood to produces a plasma of excited atoms. The plasma fluorescence is then passed via optical fiber to a CCD spectrometer. Later, these spectra are classified by comparing them against the reference fluorescence intensities (Aono et al., 2012; Solo-Gabriele et al., 2004). The distance between the specimen and the LIBS detector is on the order of a few feet. Thus, a detection window of about 8 cm is estimated for LIBS system, which simplifies the conveyor system design for feeding the sample to the detector (Solo-Gabriele et al., 2004). A summary of typical LIBS based sorting techniques is presented in Table 2.

Table 2
A summary of typical LIBS technique applied for the recovering different materials from mixed waste.

Techniques	LIPS/LIBS based method
Types of materials recovered	Aluminum alloys (Cast and Wrought), HDPE, LDPE, PS, PP, PET, PVC, CCA treated wood
Types of sensors	Nd:YAG laser, CCD spectrometer, CMOS spectrometer
Main process features	Detects composition of elements in materials based upon spectral analysis
Classification success & recovery rate (in %)	80–97
Limitations	• Significant fluctuation in signal intensity is possible, which can cause uneven energy distribution between material composition and laser pulse due to varied plasma generation • The excitation of pulse is limited to small region for elemental analysis • Sensitive to surface contamination
References	Anzano et al. (2006, 2008), Aono et al. (2012), Fellin et al. (2014), Gesing and Harbeck (2008), Gondal et al. (2007), Gornushkin et al. (2000), Grzegorzek et al. (2011), Gurell et al. (2012a,b), Hark and Harmon (2014), Hasan et al. (2011a,b), Jacobi et al. (2007), and Solo-Gabriele et al. (2004)

2.3.3. X-ray based sorting

X-ray transmission (XRT) is an indirect sorting technique (de Jong and Dalmijn, 2002; De Jong et al., 2003; Mesina et al., 2007). X-ray transmission based sorting is relatively fast, capturing X-ray images within a few milliseconds. An imaging module utilizes a high-intensity X-ray beam. When X-rays penetrate into the material, some of its energy gets absorbed by the material, while the rest is transmitted through to a detector at the bottom (shown in Fig. 8). The detected radiation can be analyzed to provide information about the atomic density of the material. X-ray sorting can be categorized into two types: Dual Energy X-ray Transmission (DE-XRT) and X-ray Fluorescence (XRF).

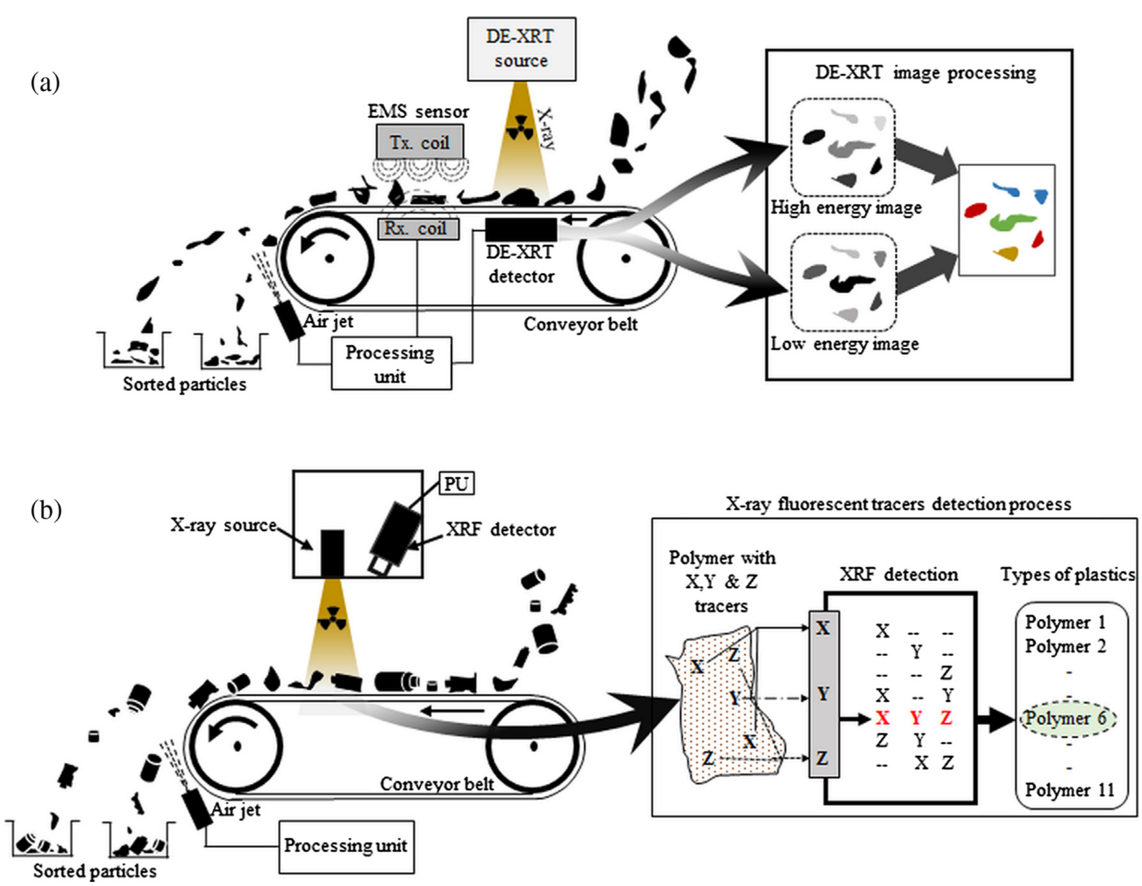

Fig. 8. (a) DE-XRT and EMS based sorting technique utilizes the property of electrical conductivity and density for classification and compressed air jet for segregation. (b) EDXRF based sorting technique.

Metal: In the recovery of metals, X-ray beam absorption depends upon the density and the thickness of the target metal fraction (Mesina et al., 2007; Rao, 2006b). The DE-XRT is a modified version of the X-ray transmission technique, wherein a dual-emission X-ray is applied to materials with different energy levels, i.e., two beams of different wavelengths (Bokun and Osadchii, 2010; Mesina et al., 2007). The attenuation of X-ray radiation is more in a higher density material medium compared to a lower density material medium. The identification of various waste fractions is performed by determining density difference (see Fig. 8(a)) using Lambert's Law (Von Ketelhodt and Bergmann, 2010).

Using a combination of different sensors (hybrid/multi-sensor combination) can improve the characterization and sorting accuracy of metal wastes (Koyanaka and Kobayashi, 2010; Mesina et al., 2007; Rahman and Bakker, 2012; Takezawa et al., 2015). The combination of DE-XRT and EMS (see Fig. 8(a)) is observed to have better efficiency and classification of material (Mesina et al., 2003; Rahman and Bakker, 2012), as compared to other standalone systems. Reportedly it is difficult to distinguish wrought and cast aluminum (Mesina et al., 2003, 2007; Takezawa et al., 2015). This problem can be solved using hybrid technology for better efficiency.

Plastic: Recovery of plastic waste fractions can be performed using XRF techniques. This technique is only applicable in recovering PVC from PET, PP, etc., (Brunner et al., 2015). The principle behind XRF technique is that the individual atoms are excited by an external laser source leading to emission of X-ray photons. The emitted photons create a unique spectral signature corresponding to the atomic weight/element type. In case of a compound like plastic the corresponding spectral signature is a superposition of the spectral signatures of the constituent elements which can be identified using machine learning techniques.

Bezati et al. (2010a, 2011a) proposed a new approach, EDXRF (Energy Dispersive X-ray Fluorescence) for sorting plastic particles based upon tracers added to the polymer matrix, which increases the sorting selectivity of polypropylene. The tracers are formed by many substances which are dispersed into the material (Bezati et al., 2010b, 2011b). Fig. 8(b) shows a schematic representation of this technique. X-ray beam is focused and passed through the small portion of the material, and it travels to the detector. The signal from the detector is then passed to the processing unit, which controls the X-ray source. The XRF spectral signal is analyzed and utilized for the separation of materials containing specific amounts of tracers (Bezati et al., 2010a,b, 2011a,b; Brunner et al., 2015). XRF is a non-destructive elemental analysis and is capable of identifying black polymers and surface contaminated fractions with X-ray penetration of up to 1 mm depth (Bezati et al., 2011a).

Wood: The X-ray fluorescence (XRF) system can effectively identify arsenic in wood waste (Hasan et al., 2011b; Moskal and Hahn, 2002; Solo-Gabriele et al., 2004). When X-ray beams are projected onto a wooden sample, a fluorescence is generated due to the relaxation of the atoms. The fluorescence released depends upon the tracers of various elements present in the wooden specimen (shown in Fig. 8(b)). Research has shown that the presence of copper, arsenic and chromium can be identified using the XRF technique (Blassino et al., 2002; Fellin et al., 2014; Hasan et al., 2011a,b; Solo-Gabriele et al., 2004).

The XRF system is composed of an X-ray tube and a solid state detector. The XRF system is mounted approximately 1 foot above the wood specimen. The X-ray tube and detector are fitted in a closed chamber, and a software driven digital pulse processor is connected to the detector (Blassino et al., 2002; Solo-Gabriele et al., 2004). The classification/identification of metals such as As, Cr, and Cu depends upon the reflection of concentrated metals in the wooden waste fragments and is detected by the XRF detector. The recovery efficiency achieved is 98%, 97% and 91% for As, Cr, and Cu respectively (Hasan et al., 2011a,b). A summary of typical X-ray based sorting techniques is presented in Table 3.

2.3.4. Optical based sorting

Traditional techniques often relied on physical properties (Mesina et al., 2003; Rao, 2006a; Rahman and Bakker, 2012; Tam, 2008) but ignored visual/tactile cues like color, shapes, texture and size for the sorting of waste. In optical sorting, camera based sensors are used for the identification of waste fractions. The following sections present some commonly used optical sorting techniques.

Metal: A hybrid system with a combination of color vision and an inductive sensor array can identify metals such as copper, brass, zinc, aluminum, and stainless steel (Kutila et al., 2005). Regions with a larger red component in an image of mixed metals indicate copper and brass, while regions of blue indicate stainless steel and aluminum. The inductive sensor measures the electrical property of metal scraps using an array of 52 inductive sensors (Kutila et al., 2005). The identification of material is based upon color differences and electrical conductivity. The hybrid technique can eliminate the limitations of other non-hybrid techniques due to surface contamination (Kutila et al., 2005).

An optical sorting technique using multivariate analysis includes a combination of a 3D shape detection camera and a weight-meter, fixed along the conveyor system (shown in Fig. 9

Table 3
A summary of typical X-ray based sorting techniques applied for recovering different materials from mixed waste.

Techniques	Types of materials recovered	Types of sensors	Main process features	Classification success & recovery rate (in %)	Limitations	References
XRT/ DEXRT and EMS method	Cast and wrought aluminum, Cu, Mg	Line scan camera, DE-XRT detector, EMS	Specific atomic density of material irrespective of size, moisture or dust is detected	90–97	• Issue in categorizing between wrought and cast aluminum (can be overcome by hybrid techniques) • DEXRT inefficient for smaller particles	Mesina et al. (2007), Von Ketelhodt and Bergmann (2010), and Takezawa et al. (2015)
XRF based	PVC	X-ray source, XRF detector	Detects elemental composition of material in the form of tracers based upon atomic density	92–96	• XRF cannot differentiate plastic types (except PVC)	Bezati et al. (2010a,b and 2011a,b)
XRF based	As, Cr, Cu treated wood	X-ray tube, solid state detector	Detect reflectance of particle signature of the material	91–98	• Identification of tracers are limited to periodic table	Blassino et al. (2002), Hasan et al. (2011a,b), and Solo-Gabriele et al. (2004)

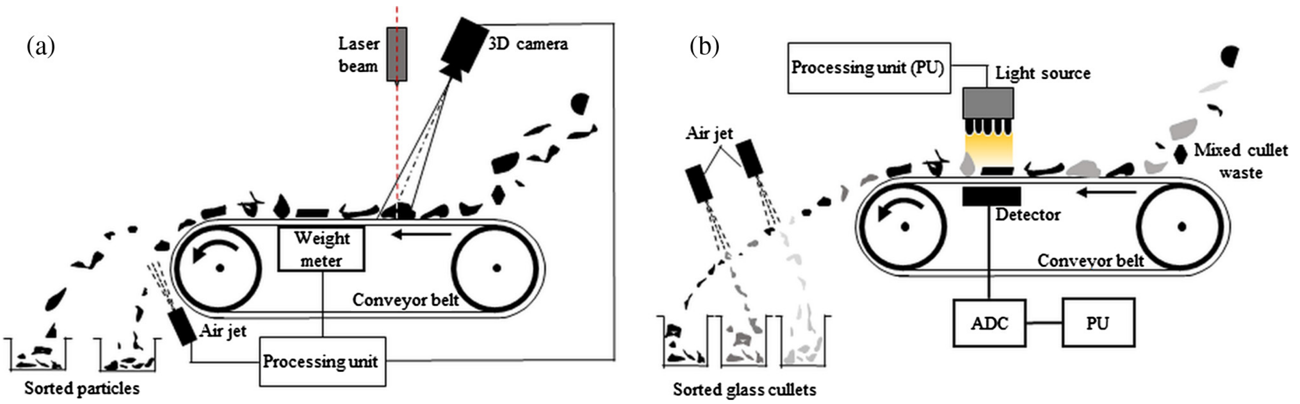

Fig. 9. (a) Optical sorting technique consisting of a 3D imaging camera, weight meter, belt conveyor and an air compressor. The 3D camera is equipped with a linear laser and optical CCD (determines the height of each fragment). A compressed air jet is used for ejecting various fractions. (b) Color sorting technique of ceramic glass contaminants composed of a light source and sensor. The sensor detects the glass cullets and generates an analog signal corresponding to the amplitude of light passed through the sample. The analog signal is converted to digital using ADC followed by determination of respective fractions and ejection into respective bins.

(a)) (Koyanaka and Kobayashi, 2010, 2011). A large number of non-ferrous (NF) metals like magnesium, wrought aluminum, and cast aluminum are recovered in this technique with a sorting efficiency of 85% (Koyanaka and Kobayashi, 2010, 2011). The accuracy of this method is not affected by surface contaminants like paint, oil, and dust. In addition, the technique can also sort highly irregular material shapes. Installation and running cost is relatively less compared to other techniques like XRT or LIBS. The modification in multivariate data makes it possible for re-learning the neural network for obtaining higher sorting accuracy (Koyanaka and Kobayashi, 2011).

Huang et al. (2010) proposed a sorting technique based on features like shape and color. This technique combines a 3D color area scan camera with a laser beam attached to the conveyor belt (see Fig. 9(a)). This technique is known as triangulation scanning, wherein a triangle is formed among the laser beam, the camera, and the laser emitter (Huang et al., 2010). The technique claims an accuracy of about 98% for NF metals and 99% for plastic fractions.

Glass: Recovery of glass fractions (cullets) can be performed using optical sorting techniques via color based classification, as glass cullets typically have pieces with various colors like red, blue, green or any combinations thereof (Afsari, 2008; Afsari and Dimsdale, 2008; Doak, 2000). In this method, the sensor scans and measures the attenuation of light of various colors which pass through the sensing region.

Fig. 9(b) illustrates a schematic representation of the color sorting technique. The figure shows that at first the unsorted glass cullets are passed through the inspection zone, where LEDs successively emit lights of red, blue and green wavelengths. Depending upon the color of the specimen, the light emitted from the LEDs undergoes attenuation (Afsari and Dimsdale, 2008; Doak, 2000). These attenuated color components are then compared against known reference colors and thereby the color of the specimen is identified. Identified cullets are then sorted into particular bins using a compressed air jet (see Section 2.2.(m)). One of the drawbacks of this technique is that it may misclassify glass samples with paper/plastic labels. This can be overcome by using infrared and ultraviolet wavelengths instead of visible wavelengths. Infrared and UV penetrate through paper labels and can help in the identification of a sample with paper labels.

The ultraviolet (UV) sorting technique is used to distinguish opaque and other special glasses (ceramic glass, lead glass, borosilicate glass, etc.) from mixed glass scrap (Huber and Leitner, 2014; Huber and Pansinger, 2011). The technique is entirely independent of the color and the shape of the glass specimen. Detection is performed by radiating UV light over the glass specimen. Based on the properties of the glass specimen, UV is absorbed and attenuated. The intensity of the attenuated UV is then compared with a standardized reference value and thereby the specimen is classified. The classified glass specimen is then diverted to a predetermined bin location with air jet nozzles as described in Section 2.2.(m) (Huber and Leitner, 2014; Huber and Pansinger, 2011).

Paper: Use of optical sorting of various types of papers from waste has been reviewed in detail elsewhere (Rahman et al., 2014). Rahman et al. (2009a,b) performed sorting of various types of papers like old corrugated cardboard (OCC), old news paper (ONP) and white paper (WP) using image processing methods. The technique transforms an image of a paper waste stream to a quantized image. Then the co-occurrence matrix is calculated from the quantized image (Pham and Alcock, 2002). Later, the paper grades are identified and segregated into their respective bins using a rule-based classifier (see Fig. 10) (Rahman et al., 2009b).

Template matching techniques transform pixel values of a captured image to a red-greenblue (RGB) value. To identify different paper grades, the transformed RGB strings are compared with the template images by searching in an N-cell (Rahman et al., 2009a). Rahman et al. (2012a) explored DNA computing based on a template matching technique for the classification of recyclable

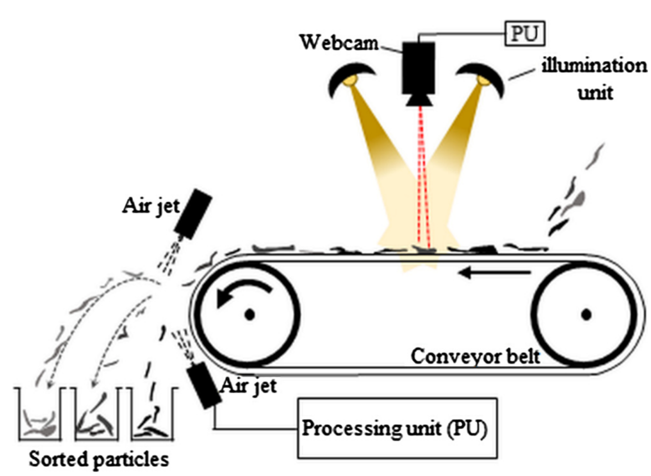

Fig. 10. The optical sorting technique consists of web-camera, conveyor belt, and air compressor. Web-camera sensor can segregate different paper grades using texture information.

Table 4
A summary of typical optical based sorting techniques for recovering of different materials from mixed waste.

Techniques	Types of materials recovered	Types of sensors	Main process features	Classification success & recovery rate (in %)	Limitations	References
Optical sorting method	Cu, Al, Mg, Zn, SS, Ni, Br	3D imaging camera, Optical CCD, Linear laser	Material color (red, green, and blue), shape and size properties detected	86–95	• Inductive sensors are sensitive to distance changes • Complex shapes of material can cause variation in measurement	Huang et al. (2010), Koyanaka and Kobayashi (2010, 2011), and Kutila et al. (2005)
Co-occurrence feature sorting	WP, ONP, OCC	Web camera (Logitech Quickcam Pro 4000)	Classification is done through rule-based classifiers and by energy for the co-occurrence matrices	90.67	• Unsuitable for real-time implementation • High computational time	Pham and Alcock (2002) and Rahman et al. (2009b)
Template matching/ DNA computing algorithm	WP, ONP, OCC	Web camera	RGB string is applied over entire pixels and template matching is done.	90–96	• Varied illumination can cause error in detection • High computational time	Rahman et al. (2009a, 2012a) and Watada (2008)
Dominant color	WP, ONP, OCC	Web camera	Features taken: Histogram scale length on the dark side, histogram scale length on the light side, energy, mode using KNN classifier and by absolute distance metric	93	• Performance is influenced by lighting conditions • Consistent illumination is required	Rahman et al. (2011)
Windows feature method with RGB color space	WP, ONP, OCC	Web camera	RGB component mode and energy taken by CBR approach: case base reasoning	95.17	–	Rahman et al. (2012b)
Windows feature with HSI color space	WP, ONP, OCC	Web camera	Mean of hue and mean of saturation are calculated by chromaticity: with window-based subdivision, distance, and voting	91.07	• Weight of the throughput depends upon the grade and size of the paper	Rahman et al. (2010, 2012a)
Optical sorting	Colored glass (red, green, blue)	Line scan camera	Properties based upon their colorintensities	–	• Possibility of misreading of colors due to film buildup • Cullet furrowing can cause non-uniformities	Afsari (2008), Afsari and Dimsdale (2008) and Doak (2000)
Ultraviolet based sorting	Ceramic glass, lead glass, borosilicate glass	Ultraviolet sensor	Material is identified based on monochromatic properties	–	• Detection of non-transparent or low-transparent impurities are not possible	Huber and Leitner (2014) and Huber and Pansinger (2011)

paper. DNA computing methods have also been explored by other researchers (Rahman et al., 2012a; Watada, 2008; Yeh and Chu, 2008).

Rahman et al. (2011) performed identification of paper grades (WP, ONP, and OCC) using the KNN classifier technique. To train the classifier, feature vectors were obtained from ten samples of each paper grade. Paper grades were then identified using the trained KNN classifier and a success rate of 93% has been reported.

A smart vision sensing (SVS) system was proposed that can identify various paper grades, namely, WP, ONP, and OCC using case-based reasoning (CBR) with window features (Rahman et al., 2010). The technique is based upon the maximum occurrence of a particular reference template in the paper image. Matching scores of reference image templates are determined, which then help in identification of respective paper grades (Rahman et al., 2010).

Another SVS system has been proposed based upon the conversion of RGB pixels of the captured image into the HSI (hue, saturation, and intensity) color scale (Rahman et al., 2010, 2012a). In this approach brightness and intensity information is ignored, overcoming the need for consistent illumination during the identification phase. An accuracy of 90% was reported using this approach (Rahman et al., 2010, 2012a). A summary of typical optical sorting techniques is presented in Table 4.

2.3.5. Spectral imaging based sorting

Spectral imaging combines both spectral reflectance measurement and image processing technologies (Picon et al., 2009, 2010; Tatzer et al., 2005). Various reported spectral imaging based techniques include NIR (near infrared), VIS (visual image spectroscopy) and HSI (hyperspectral imaging) (Bonifazi and Serranti, 2006; Jansen et al., 2012; Kreindl, 2011; Pieber et al., 2010; Serranti et al., 2006; Vegas et al., 2015).

A hyperspectral imager is similar to a laboratory spectrometer, which produces images over a continuous range of narrow spectral bands and facilitates the spectroscopic analysis of data. A schematic representation of hyperspectral sorting is shown in Fig. 11 (a). The conveyor system transports the waste fractions underneath the monitoring station, and the spectral CCD camera acquires spectral data continuously at a fixed frequency. After data pre-processing and reduction, a classification algorithm is applied to the spectral data to perform material classification (Picon et al., 2009, 2012; Tatzer et al., 2005). An array of compressed air nozzles is mounted at the end of the conveyor belt and depending

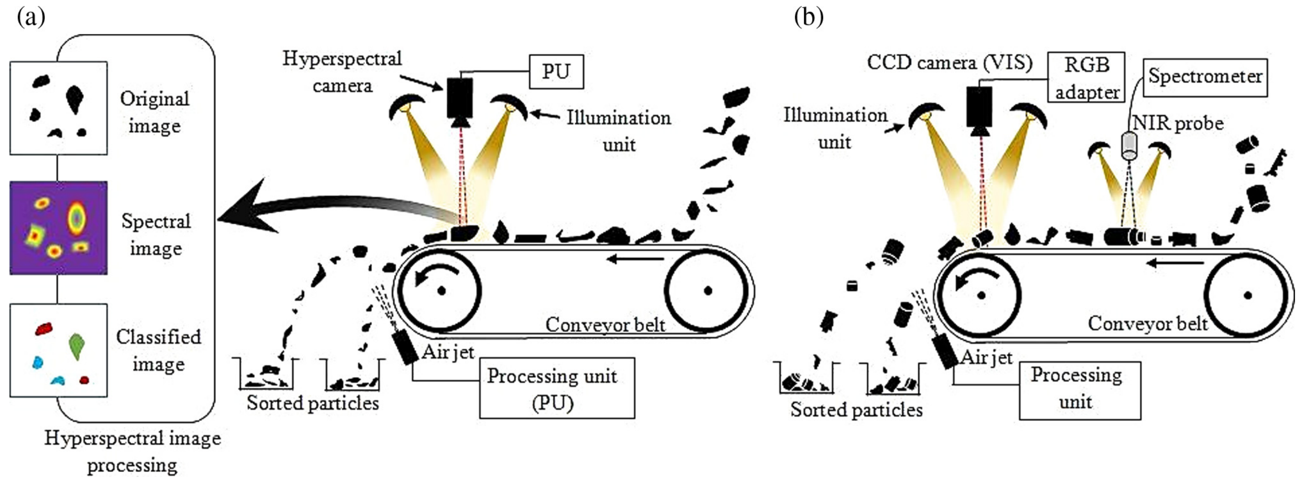

Fig. 11. (a) The hyperspectral sorting technique consists of a spectral CCD camera that identifies the particles based upon their spectral signature and segregates waste fractions into their respective bins using compressed air nozzles. (b) Spectroscopic sorting technique consists of a CCD camera and NIR spectrometer.

upon the material (see Section 2.2.(m)), individual nozzles are triggered to segregate waste fractions into their respective bins (see Fig. 11(a)) (Tatzer et al., 2005).

Metal: Picon et al. (2009) reported a classification algorithm based upon spatial and spectral feature integration in conjunction with a custom designed hyperspectral data and decorrelation scheme for the recovery of metal waste fractions (Picon et al., 2009, 2010). The FUSSER (Fuzzy Spectral and Spatial classifiER) algorithm was developed for the sorting of non-ferrous materials like aluminum, white copper, stainless steel, brass, copper, and lead, and is reported to have a classification rate of 98%. A limitation of the approach is that it fails to distinguish stainless steel if it has the same spectral information as other non-ferrous metals (Picon et al., 2009).

Plastic: In spectroscopy based techniques, light is illuminated on a plastic waste sample. Due to the interaction between light and the sample, a unique set of wavelengths of light gets reflected for each type of plastic present in the sample. Various sensors like NIR, MIR, and laser Raman are used for reading the signature of reflected wavelengths from the target material. Later, the material to be sorted out is determined by the processor unit.

Safavi et al. (2010) developed a technique by utilizing VIS reflectance spectroscopy to identify PP plastic in mixed waste. The setup consists of a material handling system and a detection unit (see Fig. 11(b)); the conveyor system is used to transport the mixed waste to the detection unit where a VIS light source illuminates the sample. The identification unit utilizes VIS spectrometer to analyze the reflected light from the sample and determine the materials present in the sample. The compressed air nozzle ejects the particles into their respective bins as described in Section 2.2.(m) (Safavi et al., 2010).

The HSI based approach aims in classifying polyolefin particles from mixed waste by recovering PP and PE plastics with high purity in the NIR range (1000–1700 nm) (Serranti et al., 2010, 2011, 2012). Fig. 11(b) illustrates a typical spectroscopy system, wherein the HSI system is equipped with a moving conveyor belt and sensing system comprising an illumination and NIR spectral camera. First, materials are brought under the inspection zone via the conveyor. After this, the NIR camera captures an image of the sample. The image is then processed using a classification algorithm.

Various approaches for improving the performance of the classification algorithm have been reported. It has been reported the use of principal component analysis (PCA) to reduce the dimensionality for classification of the spectral data obtained from the NIR image (Serranti et al., 2011, 2012). Kassouf et al. (2014) developed a fast way of classifying plastics like PET, PE, PP, PS and polylactide (PLA) by a combination of MIR spectroscopy along with independent component analysis (ICA). In addition to this, a more accurate classification was obtained by separating plastic waste belonging to a specific family of polymer e.g., LDPE and HDPE. Due to the high penetration depth of NIR radiation, pre-treatment of a sample is not required and the speed of measurement is often high. However, the technique cannot detect black polymer materials effectively due to their high absorptivity.

Glass: Serranti et al. (2006) proposed an approach to recognize ceramic glass using spectral signatures in the MIR range. The spectral characterization of glass and ceramic glass fractions were performed and the specific wavelength ratio of two classes of materials can be recognized using the spectral signature (Serranti et al., 2006). Bonifazi and Serranti (2006) proposed an approach for identifying and sorting between useful (glass) and pollutant (ceramic glass) materials as shown in Fig. 12. This approach utilizes the VIS and NIR spectrum, by comparing the detected materials with reference samples of glass and ceramic glass representing different shapes, thicknesses and colors.

Hyperspectral imaging based sensing devices are often installed for on-line recognition of glass and ceramic glass fractions inside

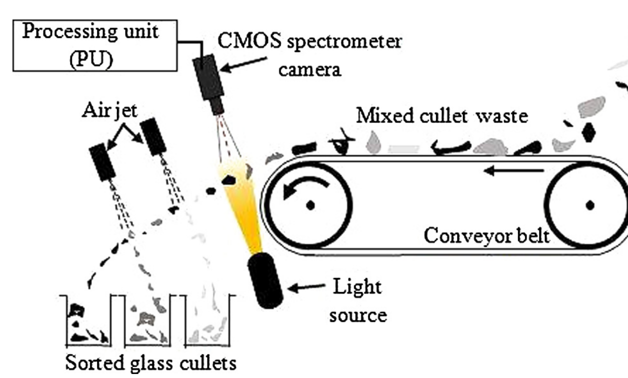

Fig. 12. On-line sorting of ceramic glass contaminants, which consists of a CMOS spectrometer camera, conveyor system and ejection system. The cullets are passed through a detection system and analyzed by their characteristic feature (usually shapes, thickness, and color) and ejected into respective bins using a compressed air jet.

Table 5
A summary of typical spectral based sorting techniques applied for recovering of different materials.

Techniques	Types of materials recovered	Types of sensors	Main process features	Classification success & recovery rate (in %)	Limitations	References
Hyperspectral based sorting	Cu, Al, Pb, SS, Brass	Spectral CCD camera	Detects spectral signature and color properties of material	95–98	• HSI fails to discriminate stainless steel if it has the same spectral information with other non-ferrous metals	Picon et al. (2009, 2010, 2011, 2012) and Tatzer et al. (2005)
Spectroscope analysis method	PE, PET, PP, PS, PLA, LDPE, HDPE	NIR, MIR, VIS spectrometers	Material color (red, green and blue) and spectral signature are detected	96–98		Kassouf et al. (2014), Safavi et al. (2010), and Serranti et al. (2010, 2011, 2012)
Spectral sorting approach	Ceramic glass	CMOS spectrometer camera (NIR, VIS, HSI)	Detects spectral signature of the material	–	• VIS signal ignores material with label and surface contaminants	Bonifazi and Serranti (2006) and Serranti et al. (2006)

glass recycling plants (Bonifazi and Serranti, 2006). NIR is applied in statistical classifiers for recognizing the spectral signatures of materials. A summary of typical spectral imaging based sorting techniques is presented in Table 5.

3. Discussion

In the last 50 years, a wide variety of segregation/separation technologies such as size separation, EMS/magnetic field separation, and sensor based separation have been developed for MSW sorting. Size separation/reduction plays a vital role in pre-processing before the sorting process. Incorporation of automation techniques in MSW sorting has improved the efficiency of sorting systems in addition to the quality, consistency and safety of the recycling process (Parasuraman et al., 2000; Satchell, 1998). Based upon the level at which automation is applied, the automated sorting techniques for recycling can be broadly grouped into three levels, namely, (i) device level, (ii) machine level, and (iii) system level.

Device level: This is the lowest level, which includes actuators, sensors and other devices connected into an open loop system, which are connected into individual control loop of the machine in automated sorting system. Actuators include prime movers like, motors to drive the material handling system. Typically, sensors include eddy current and magnetic sort (Al-Salem et al., 2009; Hansen et al., 2007; Jank et al., 2015; Krivtsova et al., 2009; Svoboda, 2004; Yuan et al., 2015).

Machine level: In this level, the device level components are assembled in an individual machine and are configured in a closed loop (Brojboiu et al., 2013; Mesina et al., 2003; Rahman and Bakker, 2012).

System level: In this level, the group of machines or workstations are interconnected or supported by material handling systems, computer and other peripheral equipment. The operations performed at this level are under centralized instructions. Various machines like comminution, inspection, material handling and separation systems are coordinated for an efficient automated material handling, detection and binning (Anzano et al., 2006, 2008; Von Ketelhodt and Bergmann, 2010; Grzegorzek et al., 2011; Hasan et al., 2011a,b).

Fig. 13 illustrates the year-wise variation of the number of publications in the area of automated sorting for recycling from MSW during 2004–2015, taking into account both journal and conference publications. We have plotted the number of publications in the area of device level, machine level, and system level separately in Fig. 13 and from this we can observe that:

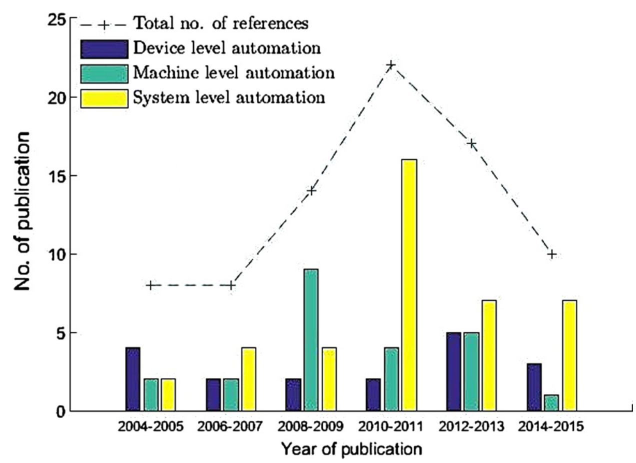

Fig. 13. Number of publications versus year of publication.

- the number of publications in the area of system level is more than the other two levels,
- there is a sharp peak in research activity in the area of system level automation between 2010 and 2011,
- the research activities in device and machine level automation has been regular, and
- there is a growing interest among researchers to move device and machine level approaches to fully automated systems.

We have discussed in detail the design aspects of various automated sorting technologies for recycling from MSW. The characteristics of sorting techniques are material diversity, accuracy, performance, robustness, flexibility, and reliability. Table 6 presents a summary of the characteristics of various sorting techniques.

Material diversity is measured in terms of the number of different recyclable materials that a particular technique can recover. Eddy current techniques sort only metals, which results in low material diversity. The accuracy of solid waste identification is a vital characteristic to determine the utility of a sorting technique. The computational performance of a system is another very important characteristic. In the case of real-time sorting, the classification algorithms need to be computationally fast for improved efficiency. The environment of a waste sorting system consists of many factors that may be uncertain and noisy. The system must provide a robust decision in rough environments; for instance, the system must be insensitive to variable illumination, vibrations,

Table 6
Overall performance of sensing technologies.

Various Technologies	Material diversity	Accuracy	Performance	Robustness	Flexibility	Reliability
Eddy current	L	M	L	H	L	H
LIBS	M	H	H	M	M	H
X-ray based	M	H	M	H	M	H
Optical based	H	M	H	L	M	M
Spectral based	H	H	H	M	M	H

L: Low, M: Medium, H: High.
Material diversity: L: <8, M: 8–12, H: >12, Accuracy: L: <90%, M: 90–96%, H: >96%, Performance: L: >1.5 m/s, M: 1.5–0.5 m/s, H: <0.5 m/s.

and dust. The system must be flexible to the user, and the users must be able to change the settings of the system as required. For reliability, the system should detect its failure automatically and then raise an alarm with necessary corrective suggestions.

We have observed that for segregating metal waste fraction, eddy current technique is most commonly utilized. Metal waste fraction is also sorted using other methods with the advent of optical, X-ray and spectral imaging based techniques. The optical and spectral based techniques have better performance with greater coverage of material varieties.

Table 7
Summary of complete automated sorting of recyclables with its work status.

Status	Types of System	References
Research	Direct sorting	Fraunholcz (2004), Kasper et al. (2015), Kelland et al. (1974), Lowell and Rose-Innes (1980), Oberteuffer (1973), Patachia et al. (2011), Rem et al. (1998), Richard et al. (2011), Svoboda (2004), Takoungsakdakun and Pongstabodee (2007), Wang et al. (2015), and Wu et al. (2013)
	Indirect sorting	Al-Salem et al. (2009), Bonifazi and Serranti (2012), Braam et al. (1988), Gaustad et al. (2012), Gesing and Harbeck (2008), Gornushkin et al. (2000), Rahman et al., (2009a,b), Pham and Alcock (2002), Safavi et al. (2010), Sattler (1990), Sattler and Yoshida (1993), Schlömann (1975), Von Ketelhodt and Bergmann (2010), and Watada (2008)
Laboratory scale	Direct sorting	Bakker et al. (2009), Cazacliu et al. (2014), de Jong and Dalmijn (1997), Hu, (2014), Jank et al. (2015), Krivtsova et al. (2009), Li et al. (2007, 2015), Pita and Castilho (2016), Wang et al. (2012, 2014), and Yuan et al. (2015
	Indirect sorting	Afsari (2008), Anzano et al. (2006, 2008), Aono et al. (2012), Bezati et al. (2010a,b, 2011a,b), Brojboiu et al. (2013), Fellin et al. (2014), Gondal et al. (2007), Gurell et al. (2012a,b), Huang et al. (2010), Huber and Pansinger (2011), Jacobi et al. (2007), Kassouf et al. (2014), Koyanaka and Kobayashi (2010, 2011), Mesina et al. (2003, 2007), Picon et al. (2009, 2010, 2011, 2012), Rahman and Bakker (2012), Rahman et al. (2010, 2011, 2012a,b), Serranti et al. (2006, 2010, 2011, 2012), Solo-Gabriele et al. (2004), Takezawa et al. (2015), and Uhl et al. (2001)
Pilot scale	Direct sorting	Hansen et al. (2007), Holloway (1989), Luciani et al. (2015), Muchova et al. (2009), Rem et al. (2012), and Vajna et al. (2010)
	Indirect sorting	Afsari and Dimsdale (2008), Blassino et al. (2002), Buchan and Yarar (1995), Doak (2000), Huber and Leitner (2014), Mesina et al. (2003), Noll et al. (2001 (2008), and Tatzer et al. (2005)
Full scale	Direct sorting	Holloway (1989), Ohara et al. (2001), Roman (1992), and Svoboda and Fujita (2003)
	Indirect sorting	Bonifazi and Serranti (2006), Grzegorzek et al. (2011), Hasan et al. (2011a,b), Kujala et al. (2015), Kutila et al. (2005), and Lukka et al. (2014)

Based on the level of development, we classify the reported automated waste sorting systems into four categories, namely, research level, laboratory prototype, pilot scale, and full-scale shown in Table 7. Research level systems are proof of concept type and the developed system is not tested extensively. Laboratory prototypes are reduced systems which are tested for a limited number of test scenarios designed in a laboratory. Pilot scale systems are those that are tested for a limited number of test cases in the production environment. In full-scale systems, extensive testing is performed in real production environment.

4. Conclusions

This paper presents a state of the art review in the area of automated sorting techniques and systems for the purpose of recycling MSW. Various elements of industrial level automation systems including material handling, imaging (NIR, MIR, VIS, X-ray, etc.), and a vast array of direct sorting techniques (magnetic, eddy current, etc.) are surveyed in this paper. In particular, this paper highlights schematics of prevalent waste sorting techniques, sensors, material handling systems and levels of automation incorporated in systems reported during 2004–2015.

We observe that most of the research advances in the area of automated waste sorting systems have taken place in developed countries. In developed countries, source segregation of waste into recyclables is very common. Therefore most of the automated waste sorting systems have been designed and are suitable only for the automated sorting of source-segregated waste. In contrast to this, source segregation is usually not implemented in developing countries due to very limited door-to-door collection and lack of motivation. As a result, the collected waste is in mixed form and is later dumped in landfill sites. After this, waste sorting is performed manually and exposes involved workers to toxic and pathogenic work environment. Therefore, a need exists to facilitate the workers involved in mixed waste sorting with automated tools to improve safety and efficiency (Paulraj et al., 2016; Takemura et al., 2006).

This opens up a research problem to develop automated systems for handling mixed waste. It must be kept in mind that the cost of automated waste sorting technology will play a significant role in its acceptability in the developing countries. Therefore, it is imperative to develop low cost and pervasive automated waste sorting technologies for solving the problem of waste management in the developing countries. The following technical challenges need to be tackled in order to achieve automated handling of MSW:

(i) *Multi-sensor fusion:* Due to the mixed nature of the waste the automated recovery of recyclables is very challenging. To increase the recovery rate, use of more than one sensor type in the detection system can be very helpful. High acquisition rates of the sensors (Kujala et al., 2015; Kutila et al., 2005; Lukka et al., 2014; Martínez et al., 2012) can be combined with available onboard computational power to develop effective systems. Sensor fusion in the area of recyclable detection from mixed waste includes the following technical challenges:

– Physical integration of sensors with the sorting systems: Most of the automated systems in this article are single sensor based systems. To identify the target waste material from an unknown environment is a non-trivial task. Focus has to be made in the proper integration of sensors at a particular location to identify and swiftly remove targeted fractions from a moving belt (Kujala et al., 2015; Lukka et al., 2014). In particular, the sensors should be integrated into the sorting platform such that sensor cross sensitivity is minimized and the overall design and fabrication is simple.
– Data fusion: Data fusion aims to overcome the limitations of individual sensors and produce accurate, reliable and robust estimation of the world state based on multisensory information (Hu and Gan, 2005). During multi-sensing operation, there are issues such as data modality, data correlation, data alignment, data association, and operational timing which make data fusion a challenging task (Khaleghi et al., 2013). Some key data fusions techniques are Bayesian inference, Markov random fields, Egomotion estimation, and Dempster–Shafer evidence theory (Axenie and Conradt, 2015; Khaleghi et al., 2013; Zhu and Basir, 2006).

(ii) *Energy-efficiency for automated systems:* An energy-efficient automated robotic system needs to be developed for recovering recyclable fractions from landfill sites. In vast landfill sites a robotic waste sorting system needs to operate for extended periods which require long term autonomy. The following challenges need to be tackled for imparting long term autonomy.

– Efficient motion planning: To improve the efficiency of power consumption during search and identification processes, an efficient motion planning and obstacle avoidance needs to be developed for a robotic system. The robot has to negotiate through the static (trees, rocks, etc.) and dynamic (humans, animals, etc.) obstacles and follow an optimum trajectory using various motion planning algorithms (Fujimura, 2012). One of the main challenges in motion planning is the disturbance caused by dynamic obstacles. Intelligent motion planning algorithms need to be developed to generate trajectory plans to deal with obstacles (Švec et al., 2014; Thakur et al., 2012).
– Robotic swarm based efficient waste sorting: Swarm based robotic systems can operate in teams and complement their individual capabilities (Barca and Sekercioglu, 2013; Brambilla et al., 2013; Patil et al., 2015). These robots have usually been tested in confined environments. However, in real world applications limited number of tests have been performed and the reported systems usually fail (Brambilla et al., 2013). To develop fail-safe systems, researchers have to develop swarm robots to tackle real-world applications like sorting and segregating recyclable waste from landfill sites, with proper coordination in motion behavior, precise navigation, and reduced energy consumption under the influence of wind and treacherous terrains (Brambilla et al., 2013).

(iii) *Robust operation under adverse environments:* The robotic systems must be capable of navigating through unknown hostile terrains (Ellery, 2005). The system must not lose stability in the case of breakdowns. The robustness of the robotic systems needs to be improved by expanding the range of operating conditions for different subsystems of the robot. Some of the challenges for improving the robustness are as follows:

– Adverse environment of landfill sites: To sort/segregate the recyclable fractions from MSW in a landfill site, the robot must be capable of handling the recyclables under adverse environments like soft terrain, moisture, wind, and dust. Due to environmental factors such as dust, sensor readings may become error-prone and thus the accuracy of mapping and recognition may get hampered (Vasilyev et al., 2015). In addition, changes in weather conditions during the operation may affect the motion of the robot performing recycling. This can be taken care of via motion planning techniques developed for handling environmental disturbances (Thakur et al., 2012).
– Dynamic obstacles: A large variety of dynamic obstacles are present in a landfill site such as humans, animals, and other vehicles. The robots should be capable of mitigating the dynamic obstacles (Fujimura, 2012).

A large body of literature has been reported in the area of automated industrial level sorting systems targeted for source-separated MSW in a regulated factory environment. A need to deal with mixed waste in large landfill sites in developing countries is opening up new research challenges for the development of robotic systems that can efficiently perform autonomous waste sorting.

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