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(54) **SORTING BETWEEN METAL ALLOYS**

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CPC ***B07C 5/3422*** (2013.01); ***B07C 5/34*** (2013.01); ***B07C 5/342*** (2013.01); *B07C 5/04* (2013.01); *B07C 2501/0054* (2013.01)

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CPC B07C 5/3422; B07C 5/34; B07C 5/342; B07C 5/04
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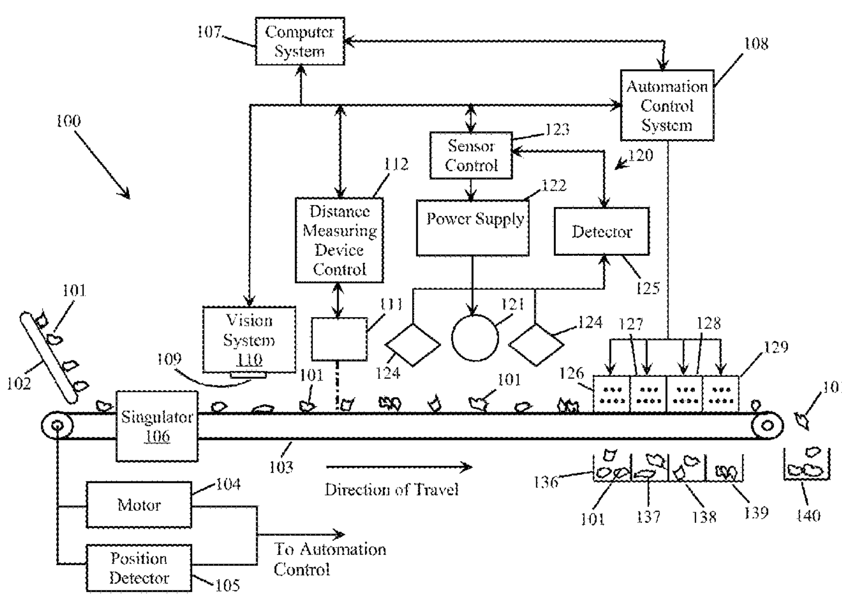
(57) **ABSTRACT**

A material sorting system sorts materials utilizing an x-ray fluorescence and/or a vision system that implements a machine learning system in order to identify or classify each of the materials, which are then sorted into separate groups based on such an identification or classification determining that the materials are composed of either wrought aluminum, extruded aluminum, or cast aluminum. The system is capable of sorting between cast aluminum alloys and also between wrought aluminum alloys.

21 Claims, 13 Drawing Sheets



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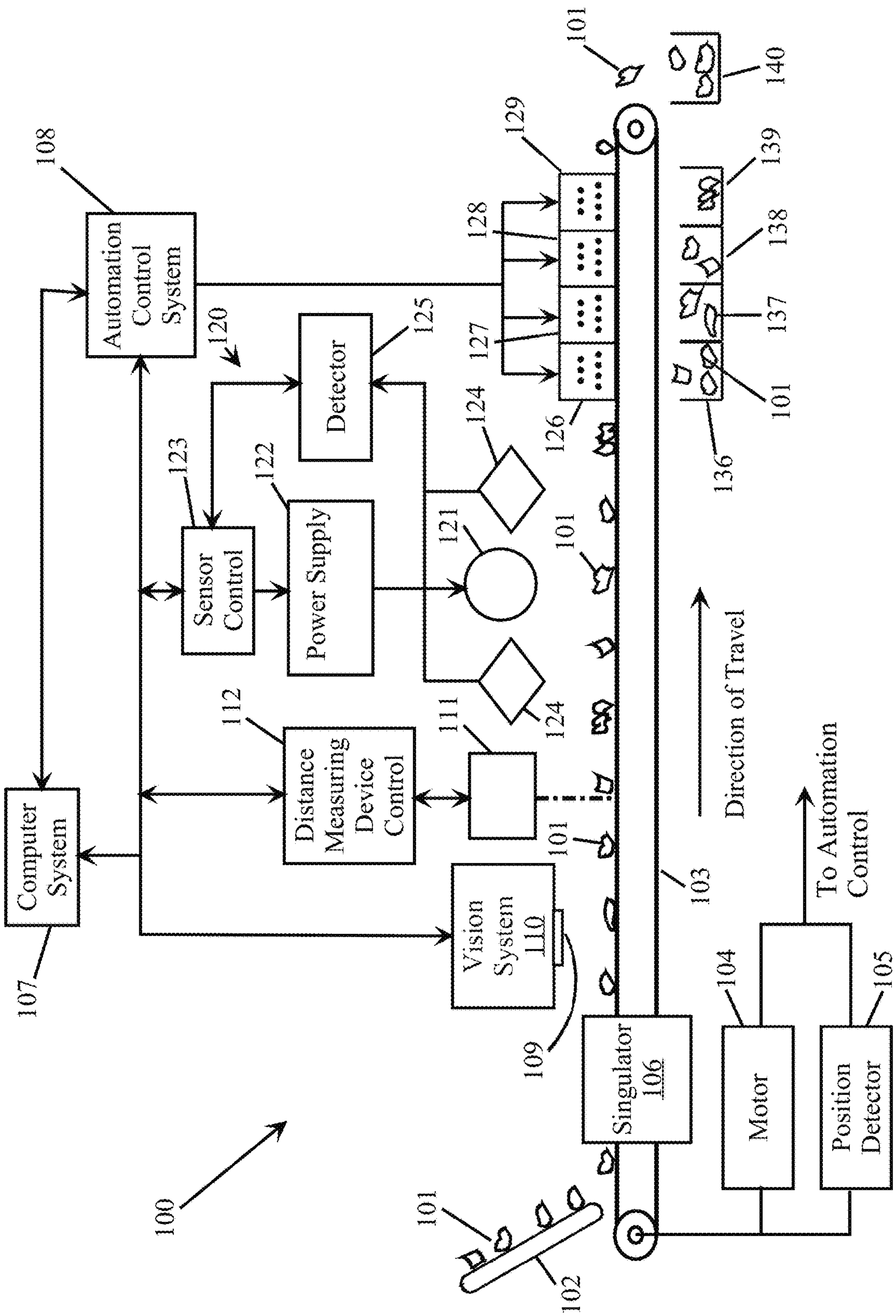

Automation Control System
108
Computer System
107
Sensor Control
123
Power Supply
122
Detector
125
120
121
124
124
Distance Measuring Device Control
112
111
Vision System 110
109
Singulator 106
Motor
104
Position Detector
105
To Automation Control
Direction of Travel
100
101
101
101
101
101
101
102
103
126
127
128
129
136
137
138
139
140

FIG. 1

Alloy	End Product	Si	Mg	Fe	Mn	Cu	Zn	Al
		%	%	%	%	%	%	%
3105	Home Siding	0.6	0.2~0.8	0.7	0.3~0.8	0.3	0.4	Remaining %
5052	Sheet Metal	0.25	2.2~2.8	0.4	0.1	0.1	0.1	Remaining %
5083	Sheet Metal	0.4	4.0~4.9	0.4	0.4~1.0	0.1	0.25	Remaining %
6061	Extrusions	0.4~0.8	0.8~1.2	0.7	0.15	0.15~0.4	0.25	Remaining %
380	Cast Engines	7.5~9.5	0.1	1.3~2.0	0.5	3.0~4.0	3.0	Remaining %

FIG. 2

Melt Test Results	Si	Mg	Fe	Mn	Cu	Zn	Al
	%	%	%	%	%	%	%
Twitch	5.2	3.05	0.46	0.26	1.48	0.78	Remaining %

FIG. 3

Composition Test Results	Si	Mg	Fe	Mn	Cu	Zn	Al
	%	%	%	%	%	%	%
Wrought-Sample 1	0.66	0.65	0.4	0.17	0.16	0.11	Remaining %
Wrought-Sample 2	0.47	0.75	0.49	0.31	0.16	0.14	Remaining %
Wrought-Average	0.56	0.7	0.45	0.24	0.16	0.12	Remaining %

FIG. 5

Composition Test Results	Si	Mg	Fe	Mn	Cu	Zn	Al
	%	%	%	%	%	%	%
Cast Fraction	7.8	0.08	1.06	0.26	2.48	0.93	Remaining %

FIG. 4

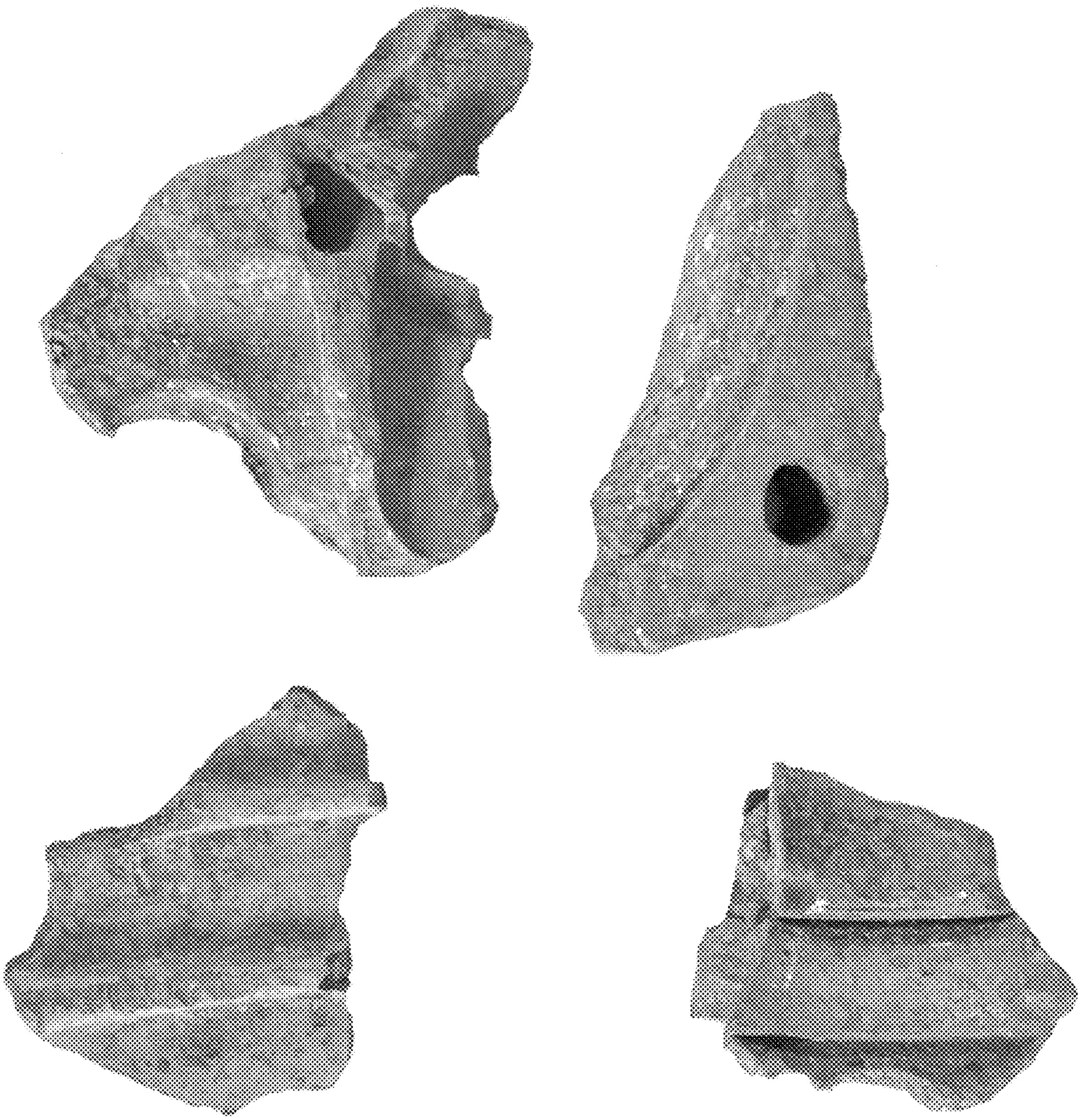

FIG. 6

FIG. 7

FIG. 8

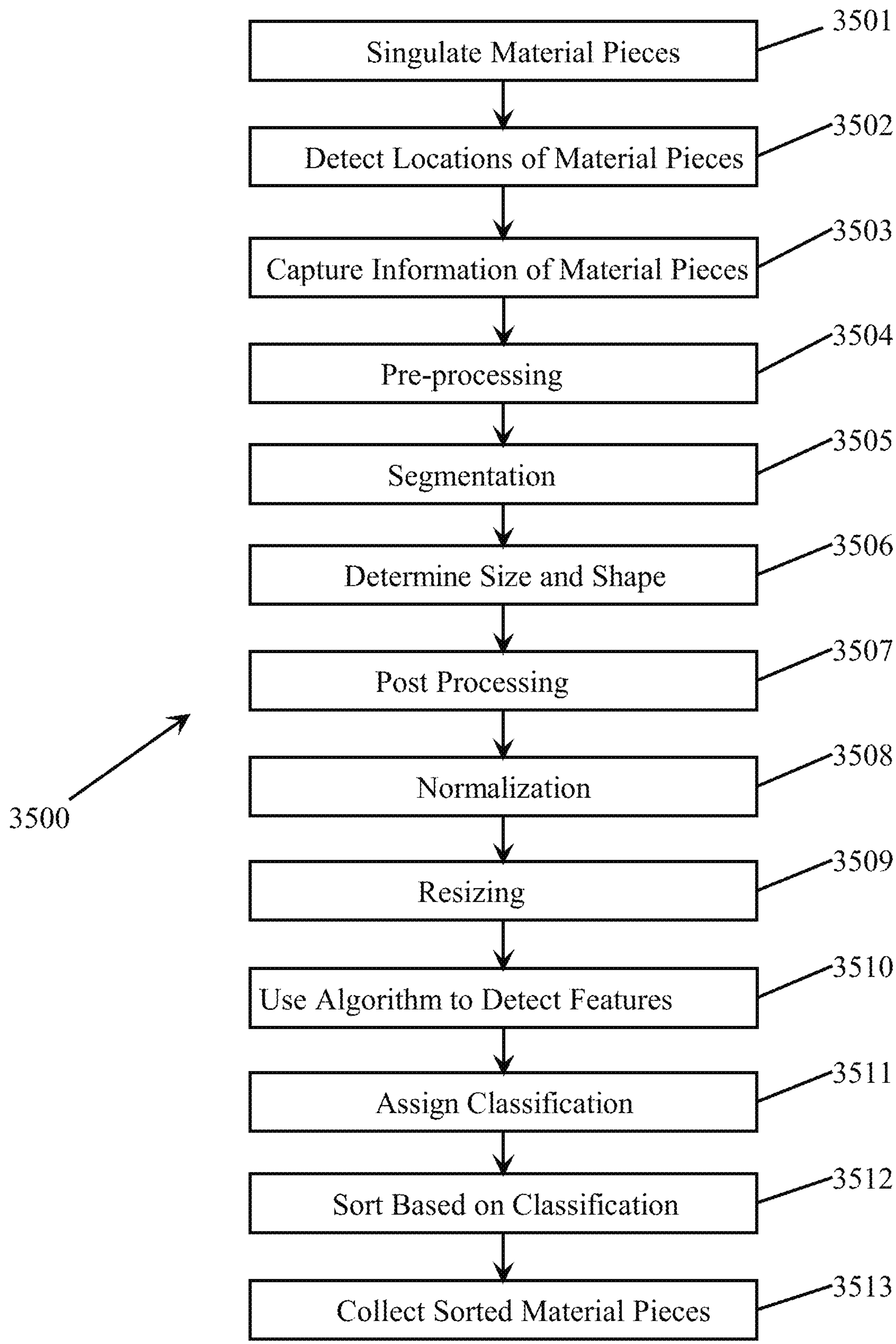
3501
Singulate Material Pieces
3502
Detect Locations of Material Pieces
3503
Capture Information of Material Pieces
3504
Pre-processing
3505
Segmentation
3506
Determine Size and Shape
3507
Post Processing
3508
Normalization
3509
Resizing
3510
Use Algorithm to Detect Features
3511
Assign Classification
3512
Sort Based on Classification
3513
Collect Sorted Material Pieces
3500

FIG. 9

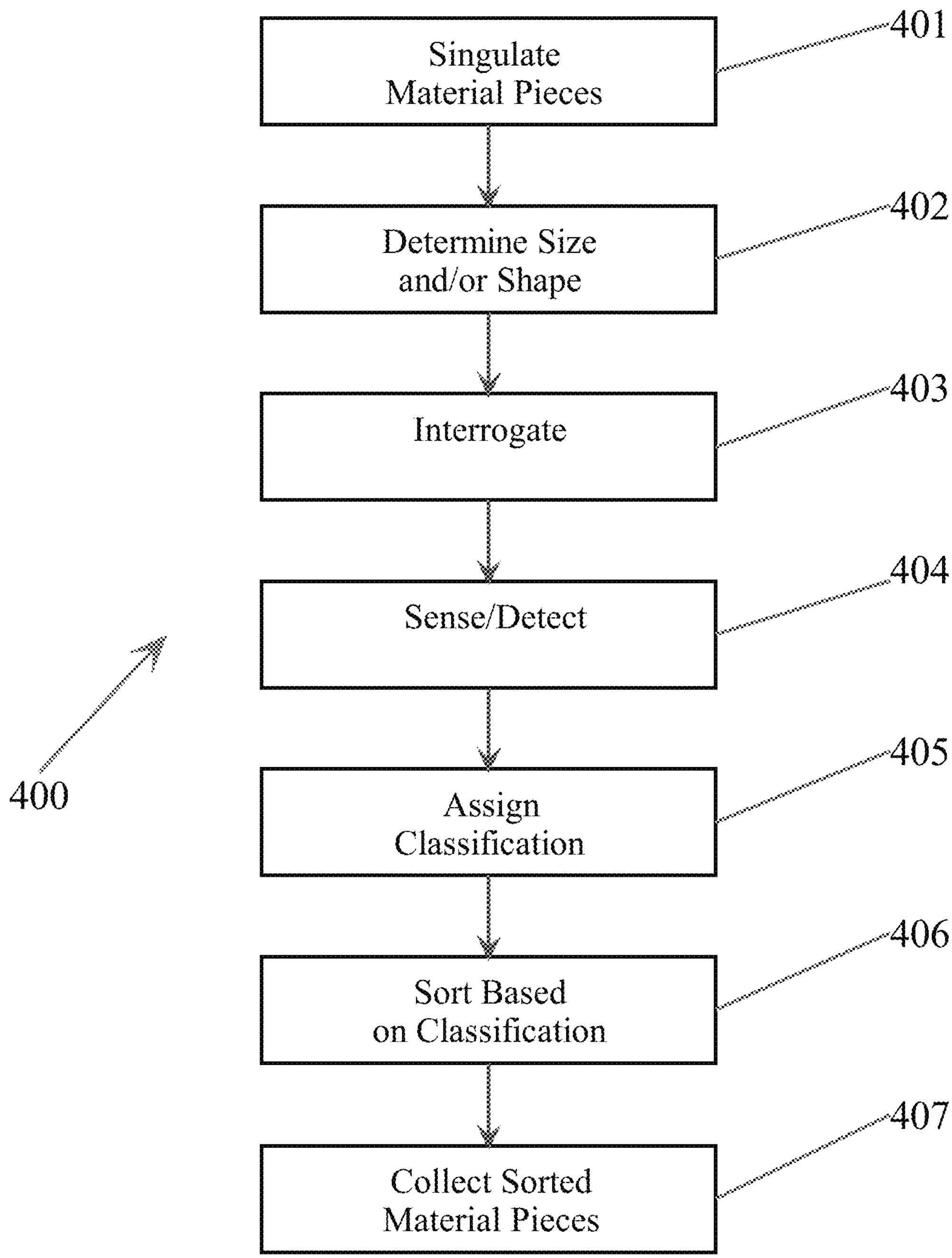
Singulate Material Pieces
401
Determine Size and/or Shape
402
Interrogate
403
Sense/Detect
404
Assign Classification
405
Sort Based on Classification
406
Collect Sorted Material Pieces
407
400

FIG. 10

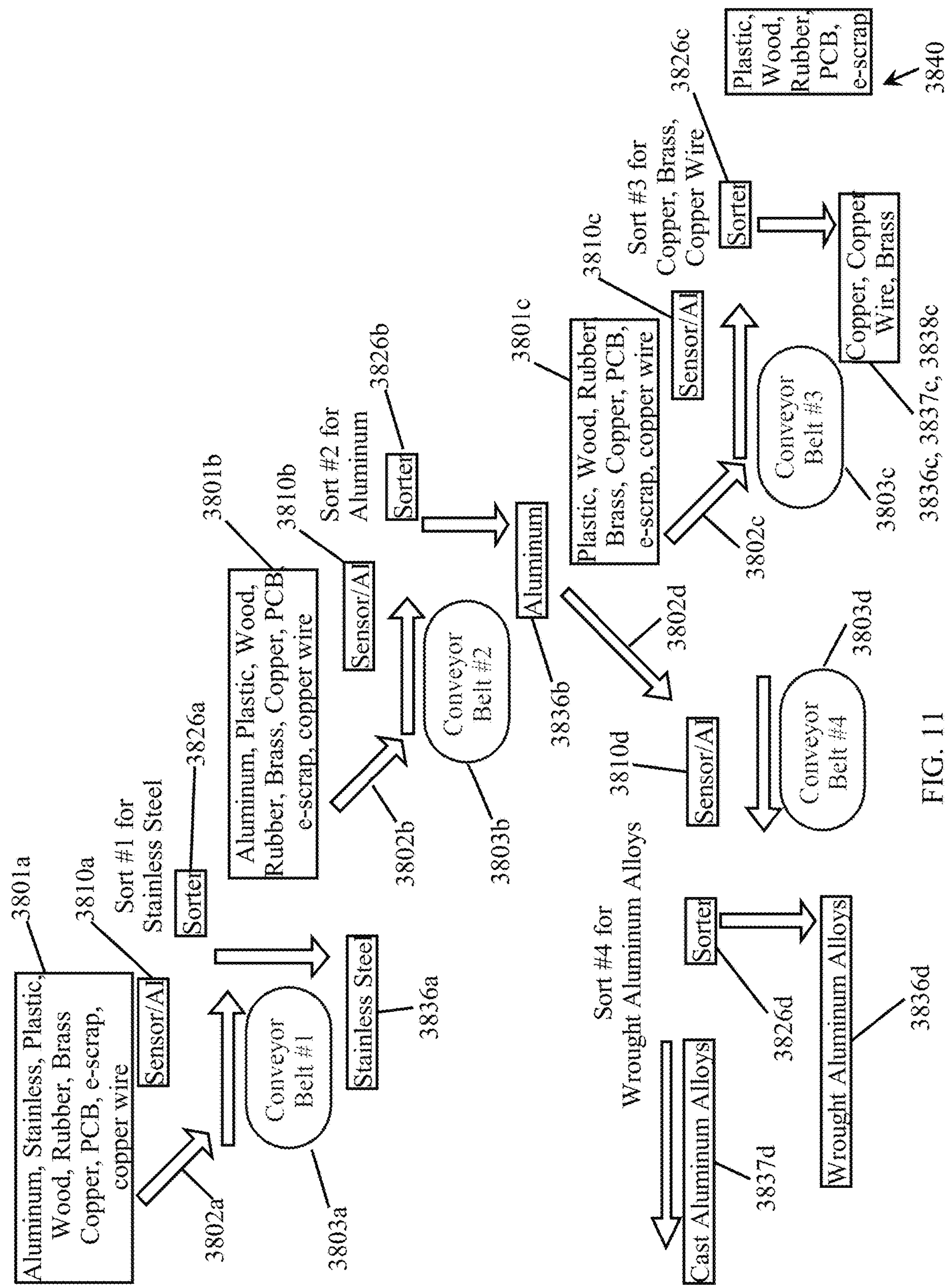
Aluminum, Stainless, Plastic, Wood, Rubber, Brass Copper, PCB, e-scrap, copper wire
3801a
3810a
Sensor/AI
Sort #1 for Stainless Steel
3826a
Sorter
3802a
Conveyor Belt #1
3803a
Stainless Steel
3836a
Aluminum, Plastic, Wood, Rubber, Brass, Copper, PCB, e-scrap, copper wire
3801b
3810b
Sensor/AI
Sort #2 for Aluminum
3826b
Sorter
3802b
Conveyor Belt #2
3803b
Aluminum
3836b
Plastic, Wood, Rubber Brass, Copper, PCB, e-scrap, copper wire
3801c
3810c
Sensor/AI
Sort #3 for Copper, Brass, Copper Wire
3826c
Sorter
3802c
Conveyor Belt #3
3803c
Copper, Copper Wire, Brass
3836c, 3837c, 3838c
Plastic, Wood, Rubber, PCB, e-scrap
3840
3802d
3810d
Sensor/AI
Conveyor Belt #4
3803d
Sort #4 for Wrought Aluminum Alloys
Sorter
3826d
Cast Aluminum Alloys
3837d
Wrought Aluminum Alloys
3836d

FIG. 11

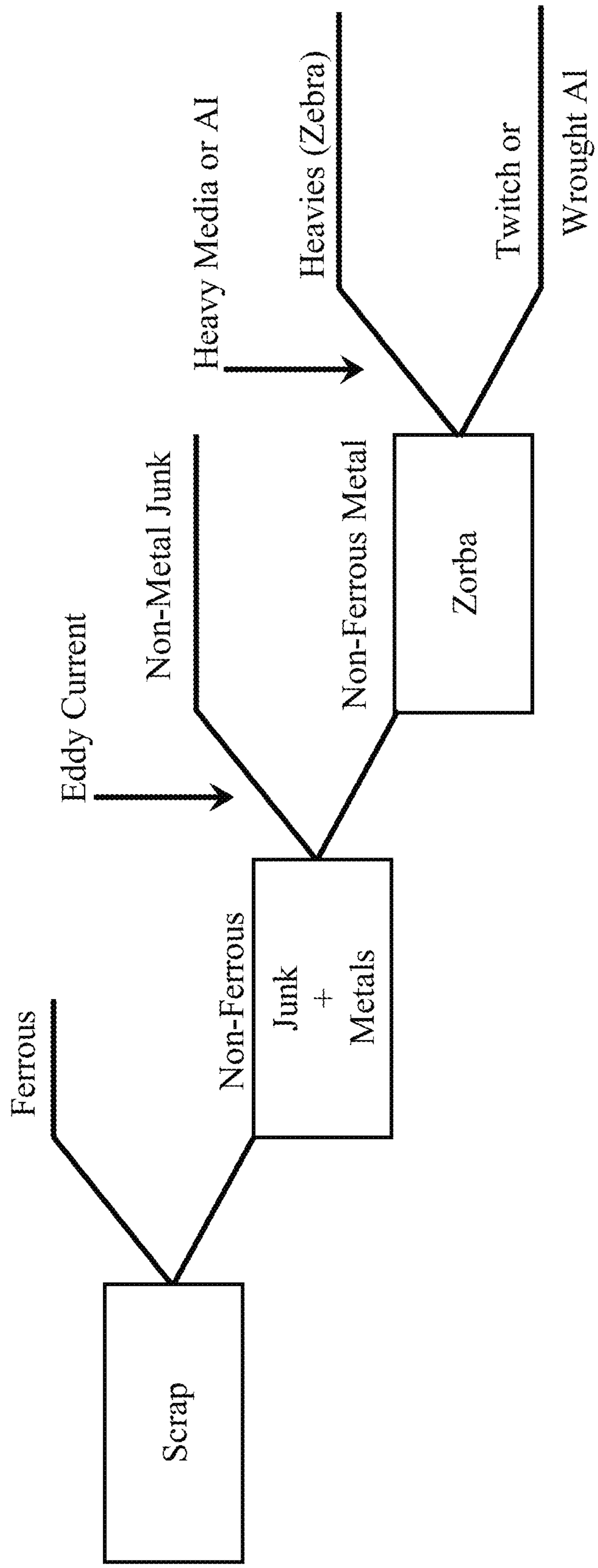
Scrap
Ferrous
Non-Ferrous
Junk
+
Metals
Eddy Current
Non-Metal Junk
Non-Ferrous Metal
Zorba
Heavy Media or Al
Heavies (Zebra)
Twitch or
Wrought Al

FIG. 12A

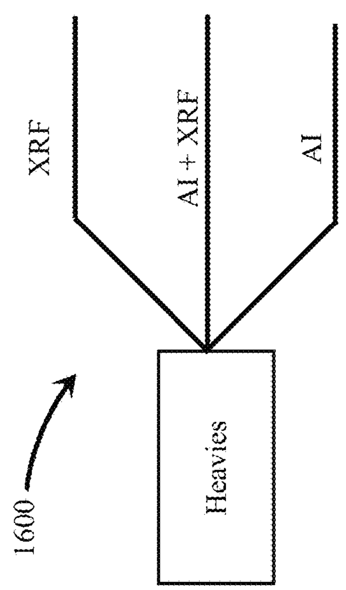

FIG. 12B

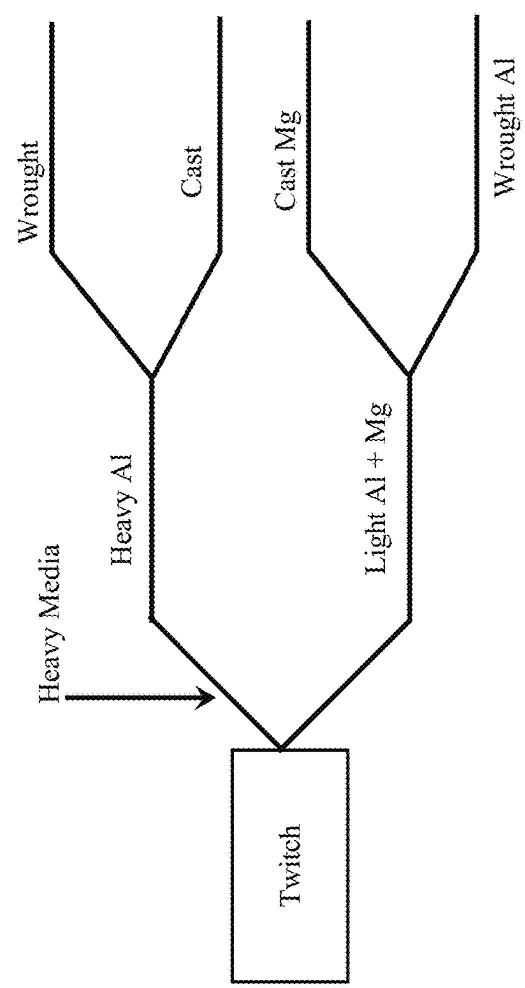

FIG. 12C

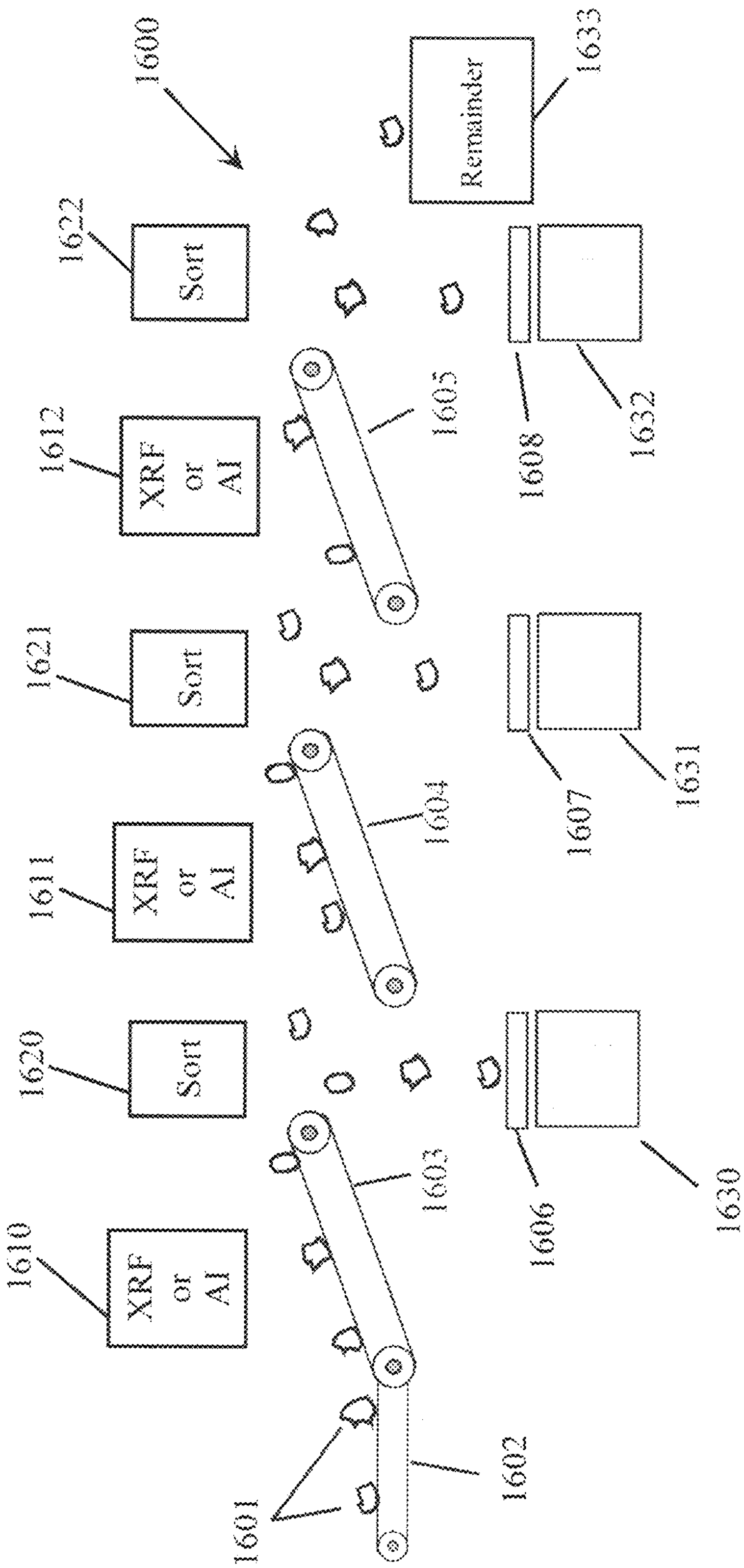
1600
Remainder
1633
1622
Sort
1612
XRF
or
AI
1605
1608
1632
1621
Sort
1611
XRF
or
AI
1604
1607
1631
1620
Sort
1603
1606
1630
1610
XRF
or
AI
1602
1601

FIG. 13A

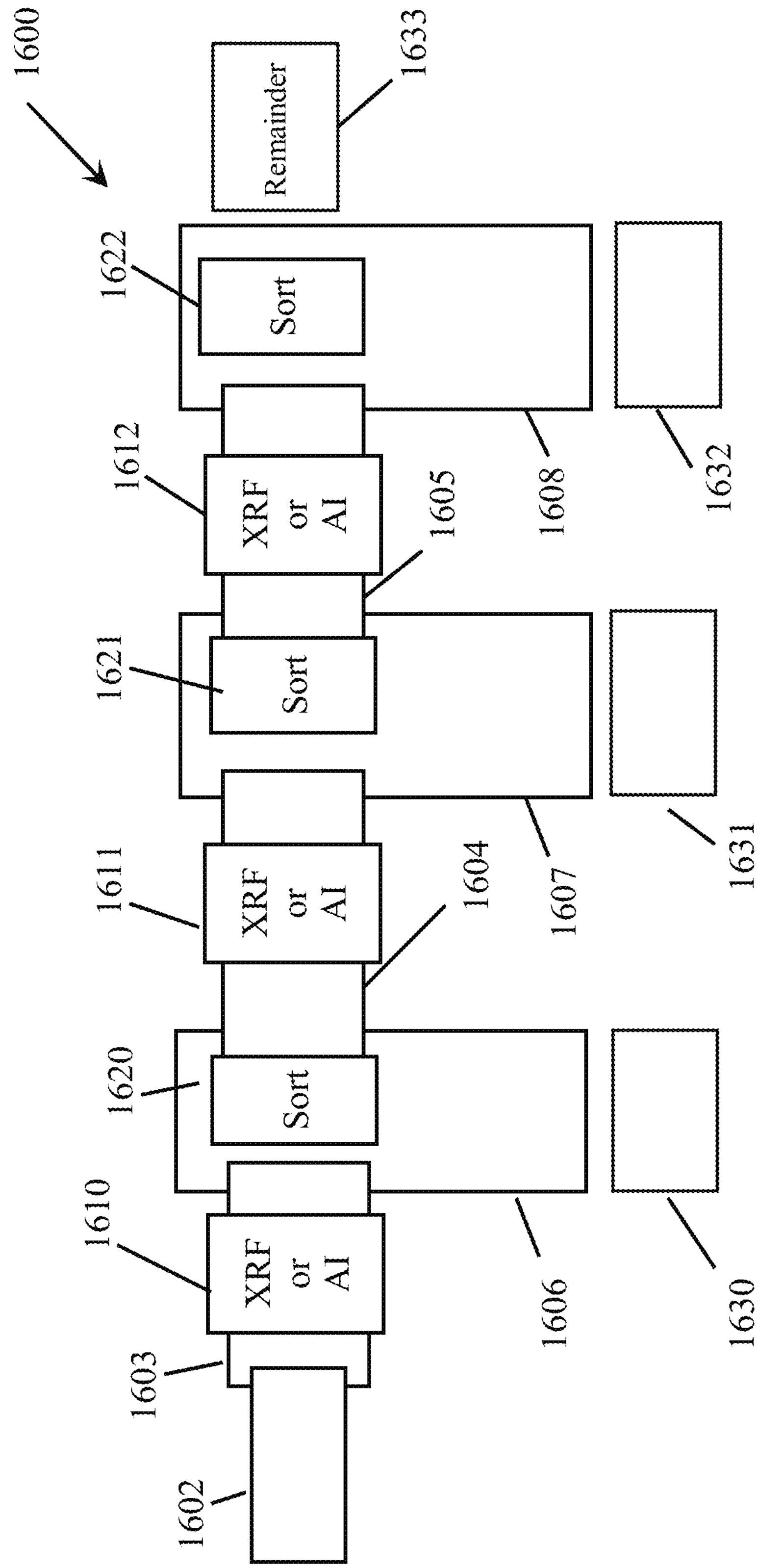
1600
1633
Remainder
1622
Sort
1612
XRF or AI
1605
1608
1632
1621
Sort
1611
XRF or AI
1604
1607
1631
1620
Sort
1610
XRF or AI
1606
1630
1603
1602

FIG. 13B

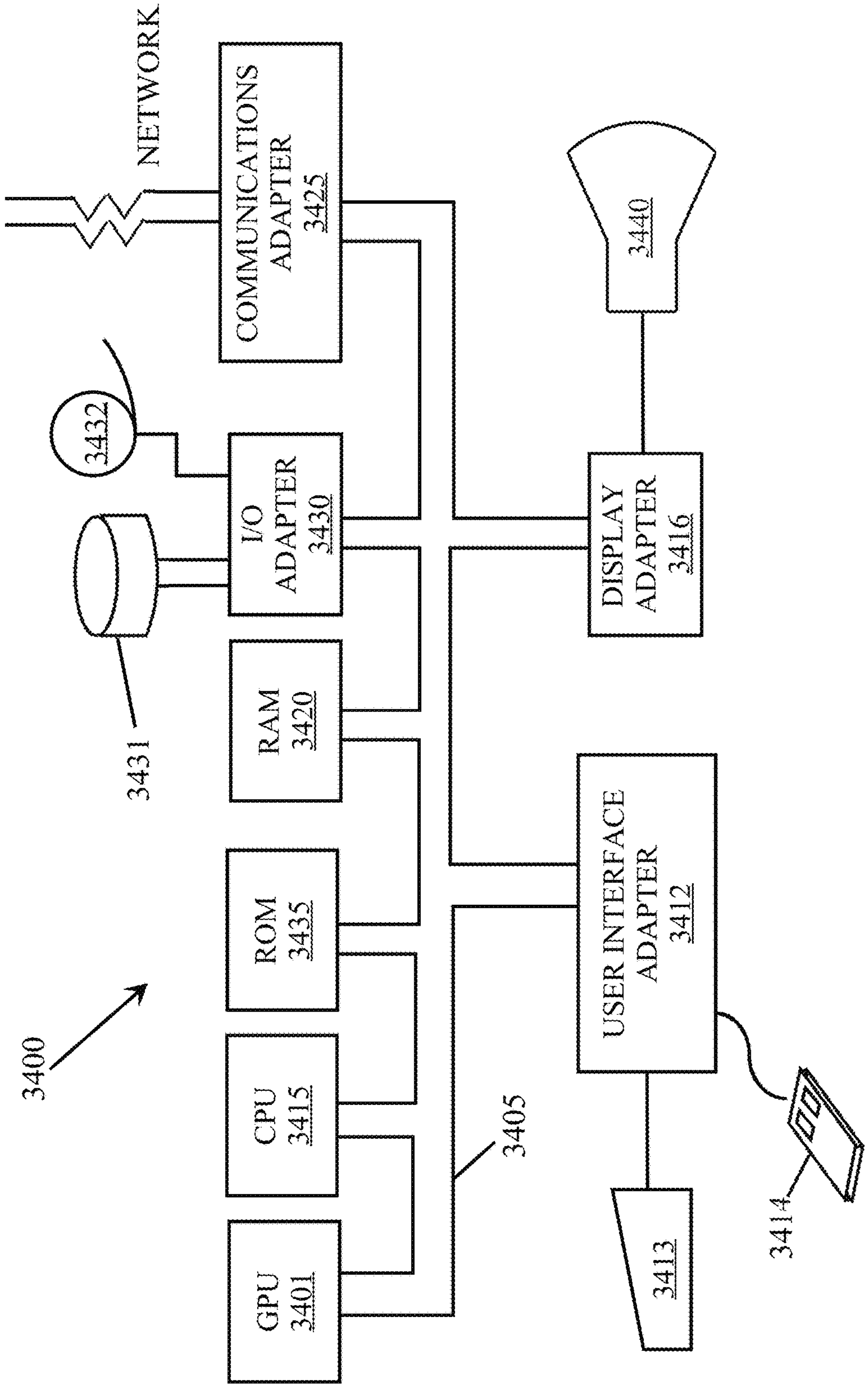
NETWORK
COMMUNICATIONS ADAPTER 3425
3432
I/O ADAPTER 3430
3431
RAM 3420
ROM 3435
CPU 3415
GPU 3401
3400
3405
3440
DISPLAY ADAPTER 3416
USER INTERFACE ADAPTER 3412
3413
3414

FIG. 14

SORTING BETWEEN METAL ALLOYS

This application is a continuation of U.S. patent application Ser. No. 17/227,245, which is a continuation-in-part application of U.S. patent application Ser. No. 16/939,011 (issued as U.S. Pat. No. 11,471,916), which is a continuation application of U.S. patent application Ser. No. 16/375,675 (issued as U.S. Pat. No. 10,722,922), which is a continuation-in-part application of U.S. patent application Ser. No. 15/963,755 (issued as U.S. Pat. No. 10,710,119), which claims priority to U.S. Provisional Patent Application Ser. No. 62/490,219, and which is a continuation-in-part application of U.S. patent application Ser. No. 15/213,129 (issued as U.S. Pat. No. 10,207,296), which claims priority to U.S. Provisional Patent Application Ser. No. all of which are hereby incorporated by reference herein.

GOVERNMENT LICENSE RIGHTS

This disclosure was made with U.S. government support under Grant No. DE-AR0000422 awarded by the U.S. Department of Energy. The U.S. government may have certain rights in this disclosure.

TECHNOLOGY FIELD

The present disclosure relates in general to the sorting of metals, and in particular, to the sorting between aluminum cast alloys, extruded aluminum alloys, and aluminum wrought alloys.

BACKGROUND INFORMATION

This section is intended to introduce various aspects of the art, which may be associated with exemplary embodiments of the present disclosure. This discussion is believed to assist in providing a framework to facilitate a better understanding of particular aspects of the present disclosure. Accordingly, it should be understood that this section should be read in this light, and not necessarily as admissions of prior art.

Recycling is the process of collecting and processing materials that would otherwise be thrown away as trash, and turning them into new products. Recycling has benefits for communities and for the environment, since it reduces the amount of waste sent to landfills and incinerators, conserves natural resources, increases economic security by tapping a domestic source of materials, prevents pollution by reducing the need to collect new raw materials, and saves energy. After collection, recyclables are generally sent to a material recovery facility to be sorted, cleaned, and processed into materials that can be used in manufacturing.

The recycling of aluminum (Al) scrap is a very attractive proposition in that up to 95% of the energy costs associated with manufacturing can be saved when compared with the laborious extraction of the more costly primary aluminum. Primary aluminum is defined as aluminum originating from aluminum-enriched ore, such as bauxite. At the same time, the demand for aluminum is steadily increasing in markets, such as car manufacturing, because of its lightweight properties. As a result, there are certain economies available to the aluminum industry by developing a well-planned yet simple recycling plan or system. The use of recycled material would be a less expensive metal resource than a primary source of aluminum. As the amount of aluminum sold to the automotive industry (and other industries) increases, it will become increasingly necessary to use recycled aluminum to supplement the availability of primary aluminum.

Correspondingly, it is particularly desirable to efficiently separate aluminum scrap metals into alloy families, since mixed aluminum scrap of the same alloy family is worth much more than that of indiscriminately mixed alloys. For example, in the blending methods used to recycle aluminum, any quantity of scrap composed of similar, or the same, alloys and of consistent quality, has more value than scrap consisting of mixed aluminum alloys. Within such aluminum alloys, aluminum will always be the bulk of the material. However, constituents such as copper, magnesium, silicon, iron, chromium, zinc, manganese, and other alloy elements provide a range of properties to alloyed aluminum and provide a means to distinguish one aluminum alloy from the other.

The Aluminum Association is the authority that defines the allowable limits for aluminum alloy chemical composition. The data for the aluminum wrought alloy chemical compositions is published by the Aluminum Association in "International Alloy Designations and Chemical Composition Limits for Wrought Aluminum and Wrought Aluminum Alloys," which was updated in January 2015, and which is incorporated by reference herein. In general, according to the Aluminum Association, the 1xxx series of wrought aluminum alloys is composed essentially of pure aluminum with a minimum 99% aluminum content by weight; the 2xxx series is wrought aluminum principally alloyed with copper (Cu); the 3xxx series is wrought aluminum principally alloyed with manganese (Mn); the 4xxx series is wrought aluminum alloyed with silicon (Si); the 5xxx series is wrought aluminum primarily alloyed with magnesium (Mg); the 6xxx series is wrought aluminum principally alloyed with magnesium and silicon; the 7xxx series is wrought aluminum primarily alloyed with zinc (Zn); and the 8xxx series is a miscellaneous category.

The Aluminum Association also has a similar document for cast aluminum alloys. The 1xx series of cast aluminum alloys is composed essentially of pure aluminum with a minimum 99% aluminum content by weight; the 2xx series is cast aluminum principally alloyed with copper; the 3xx series is cast aluminum principally alloyed with silicon plus copper and/or magnesium; the 4xx series is cast aluminum principally alloyed with silicon; the 5xx series is cast aluminum principally alloyed with magnesium; the 6xx series is an unused series; the 7xx series is cast aluminum principally alloyed with zinc; the 8xx series is cast aluminum principally alloyed with tin; and the 9xx series is cast aluminum alloyed with other elements. Examples of cast alloys utilized for automotive parts include 380, 384, 356, 360, and 319. For example, recycled cast alloys 380 and 384 can be used to manufacture vehicle engine blocks, transmission cases, etc. Recycled cast alloy 356 can be used to manufacture aluminum alloy wheels. And, recycled cast alloy 319 can be used to manufacture transmission blocks.

In general, wrought aluminum alloys have a higher magnesium concentration than cast aluminum alloys, and cast aluminum alloys have a higher silicon concentration than wrought aluminum alloys.

Furthermore, the presence of commingled pieces of different alloys in a body of scrap limits the ability of the scrap to be usefully recycled, unless the different alloys (or, at least, alloys belonging to different compositional families such as those designated by the Aluminum Association) can be separated prior to re-melting. This is because, when commingled scrap of a plurality of different alloy compositions or composition families is re-melted, the resultant molten mixture contains proportions of the principal alloy and elements (or the different compositions) that are too high to satisfy the compositional limitations required in any particular commercial alloy.

Moreover, as evidenced by the production and sale of the Ford F-**150** pickup having a considerable increase in its body and frame parts composed of aluminum instead of steel, it is additionally desirable to recycle sheet metal scrap (e.g., wrought aluminum of certain alloy compositions), including that generated in the manufacture of automotive components from sheet aluminum. Recycling of the scrap involves re-melting the scrap to provide a body of molten metal that can be cast and/or rolled into useful aluminum parts for further production of such vehicles. However, automotive manufacturing scrap (and metal scrap from other sources such as airplanes and commercial and household appliances) often includes a mixture of scrap pieces of wrought and cast pieces and/or two or more aluminum alloys differing substantially from each other in composition. Thus, those skilled in the aluminum alloy art will appreciate the difficulties of separating aluminum alloys, especially alloys that have been worked, such as cast, forged, extruded, rolled, and generally wrought alloys, into a reusable or recyclable worked product.

Two examples of aluminum alloys used in automotive manufacturing are 5052 and 6061 series alloys; their respective chemical compositions are shown in FIG. **2**. Four examples of cast aluminum alloys include 319, 383, 380, and 360; the chemical composition of cast alloy 380 is also shown in FIG. **2**, while the compositions of the others are well-known and publicly available.

Currently, the only existing technology which separates cast from wrought in a cost-effective fashion is an x-ray transmission ("XRT") technology. Because cast is heavier than wrought due to the higher silicon concentration, the cast alloys are denser than the wrought alloys. The x-ray transmission technology is able to measure the heavier density cast aluminum alloys and then sort the cast from the wrought alloys.

However, this method is not perfect. For example, cast alloys 319 and 383 have a relatively high zinc concentration (e.g., ~3%), giving these cast alloys their higher respective density. Cast alloy 360 however, has a lower relative zinc concentration (e.g., ~0.5%), and therefore lower density. The lower density of cast alloy 360 causes the x-ray transmission method to classify this alloy as a wrought alloy and not a cast alloy. Therefore, the x-ray transmission technology does not classify all of the cast alloys correctly due to the large variance in their respective densities. Thus, such cast alloys end up being sorted along with the wrought aluminum alloys, which will result in too much relative silicon in the melted mixture.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** illustrates a schematic of a sorting system configured in accordance with embodiments of the present disclosure.

FIG. **2** illustrates a table listing chemical composition limits for common aluminum alloys used for various end products.

FIG. **3** illustrates a table listing data obtained from a melt test of a batch of Twitch.

FIG. **4** illustrates a table listing an exemplary composition obtained from a clean cast fraction.

FIG. **5** illustrates a table listing percentages of metals in a composition obtained from a melt test of wrought scrap pieces sorted from Twitch in accordance with embodiments of the present disclosure.

FIG. **6** shows visual images of exemplary material pieces from cast aluminum.

FIG. **7** shows visual images of exemplary material pieces from aluminum extrusions.

FIG. **8** shows visual images of exemplary material pieces from wrought aluminum.

FIG. **9** illustrates a flowchart diagram configured in accordance with embodiments of the present disclosure.

FIG. **10** illustrates a flowchart diagram configured in accordance with embodiments of the present disclosure.

FIG. **11** illustrates linking of successive sorting systems in accordance with certain embodiments of the present disclosure.

FIGS. **12**A, **12**B and **12**C illustrate systems and processes for sorting materials for recycling.

FIGS. **13**A and **13**B illustrate systems and processes for sorting of heavy metals in accordance with certain embodiments of the present disclosure.

FIG. **14** illustrates a block diagram of a data processing system configured in accordance with embodiments of the present disclosure.

DETAILED DESCRIPTION

Various detailed embodiments of the present disclosure are disclosed herein. However, it is to be understood that the disclosed embodiments are merely exemplary of the disclosure, which may be embodied in various and alternative forms. The figures are not necessarily to scale; some features may be exaggerated or minimized to show details of particular components. Therefore, specific structural and functional details disclosed herein are not to be interpreted as limiting, but merely as a representative basis for teaching one skilled in the art to employ various embodiments of the present disclosure.

As used herein, a "material" may include a chemical element, a compound or mixture of chemical elements, or a compound or mixture of a compound or mixture of chemical elements, wherein the complexity of a compound or mixture may range from being simple to complex. As used herein, "element" means a chemical element of the periodic table of elements, including elements that may be discovered after the filing date of this application. Classes of materials may include metals (ferrous and nonferrous), metal alloys, plastics (including, but not limited to PCB, HDPE, UHMWPE, and various colored plastics), rubber, foam, glass (including, but not limited to borosilicate or soda lime glass, and various colored glass), ceramics, paper, cardboard, Teflon, PE, bundled wires, insulation covered wires, rare earth elements, etc. As used herein, the term "aluminum" refers to aluminum metal and aluminum-based alloys, viz., alloys containing more than 50% by weight aluminum (including those classified by the Aluminum Association). Within this disclosure, the terms "scrap," "scrap pieces," "materials," "material pieces," and "pieces" may be used interchangeably. As used herein, a material piece or scrap piece referred to as having a metal alloy composition is a metal alloy having a particular chemical composition that distinguishes it from other metal alloys.

As defined within the Guidelines for Nonferrous Scrap promulgated by the Institute Of Scrap Recycling Industries, Inc., the term "Zorba" is the collective term for shredded nonferrous metals, including, but not limited to, those originating from end-of-life vehicles ("ELVs") or waste electronic and electrical equipment ("WEEE"). The Institute Of Scrap Recycling Industries, Inc. ("ISRI") in the United States established the specifications for Zorba. In Zorba, each scrap piece may be made up of a combination of the nonferrous metals: aluminum, copper, lead, magnesium, stainless steel, nickel, tin, and zinc, in elemental or alloyed (solid) form. Furthermore, the term "Twitch" shall mean fragmented aluminum scrap. Twitch may be produced by a float process whereby the aluminum scrap floats to the top because heavier metal scrap pieces sink (for example, in some processes, sand may be mixed in to change the density of the water in which the scrap is immersed).

As used herein, the terms "identify" and "classify," and the terms "identification" and "classification," and their derivative forms, may be utilized interchangeably. For example, in accordance with certain embodiments of the present disclosure, an x-ray fluorescence ("XRF") system and/or a vision system (e.g., with a machine learning system as further described herein) may be configured to collect any type of information that can be utilized within a sorting system to selectively sort material pieces. As used herein, "manufacturing type" refers to the type of manufacturing process by which the material in a material piece was manufactured, such as a metal part having been formed by a wrought process, having been cast (including, but not limited to, expendable mold casting, permanent mold casting, and powder metallurgy), having been forged, a material removal process, extruded, etc.

As referred to herein, a "conveyor system" may be any known piece of mechanical handling equipment that moves materials from one location to another, including, but not limited to, an aero-mechanical conveyor, automotive conveyor, belt conveyor, belt-driven live roller conveyor, bucket conveyor, chain conveyor, chain-driven live roller conveyor, drag conveyor, dust-proof conveyor, electric track vehicle system, flexible conveyor, gravity conveyor, gravity skatewheel conveyor, lineshaft roller conveyor, motorized-drive roller conveyor, overhead I-beam conveyor, overland conveyor, pharmaceutical conveyor, plastic belt conveyor, pneumatic conveyor, screw or auger conveyor, spiral conveyor, tubular gallery conveyor, vertical conveyor, vibrating conveyor, and wire mesh conveyor.

The material sorting systems described herein according to certain embodiments of the present disclosure receive a heterogeneous mixture of a plurality of material pieces, wherein at least one material within this heterogeneous mixture includes a composition of elements (e.g., a metal alloy composition) different from one or more other materials and/or at least one material within this heterogeneous mixture was manufactured differently from one or more other materials. Though all embodiments of the present disclosure may be utilized to sort any types or classes of materials as defined herein, certain embodiments of the present disclosure are hereinafter described for sorting metal alloy material pieces, including aluminum alloy material pieces, and including between wrought, extruded, and/or cast aluminum alloy material pieces.

It should be noted that the materials to be sorted may have irregular sizes and shapes (e.g., see FIGS. **6**-**8**). For example, such material (e.g., Zorba and/or Twitch) may have been previously run through some sort of shredding mechanism that chops up the materials into such irregularly shaped and sized pieces (producing scrap pieces), which may then be fed or diverted onto a conveyor system.

Embodiments of the present disclosure will be described herein as sorting material pieces into such separate groups by physically depositing (e.g., ejecting or diverting) the material pieces into separate receptacles or bins, or onto another conveyor system, as a function of user-defined groupings (e.g., material type classifications). As an example, within certain embodiments of the present disclosure, scrap pieces or materials may be sorted in order to separate scrap pieces or materials composed of a particular metal alloy composition, or compositions, from other material pieces composed of a different metal alloy composition, and/or certain scrap pieces or materials manufactured according to one process from other scrap pieces or materials manufactured from a different process even though their compositions are indistinguishable.

Moreover, certain embodiments of the present disclosure may sort aluminum alloy material pieces into separate bins so that substantially all of the aluminum alloy material pieces having a composition falling within one of the aluminum alloy series published by the Aluminum Association are sorted into a single bin (for example, a bin may correspond to one or more particular aluminum alloy series (e.g., 1000, 2000, 3000, 4000, 5000, 6000, 7000, 8000, 100, 200, 300, 400, 500, 600, 700, 800, 900)). Furthermore, as will be described herein, certain embodiments of the present disclosure may be configured to sort aluminum alloy material pieces into separate bins as a function of a classification of their alloy composition even if such alloy compositions fall within the same Aluminum Association series. As a result, the sorting system in accordance with certain embodiments of the present disclosure can classify and sort aluminum alloy material pieces having compositions that would all classify them into a single aluminum alloy series (e.g., the 300 series or the 500 series) into separate bins as a function of their aluminum alloy composition. For example, certain embodiments of the present disclosure can classify and sort into separate bins aluminum alloy material pieces classified as cast aluminum alloy 319 separate from aluminum alloy material pieces classified as cast aluminum alloy 380.

FIG. **1** illustrates an example of a material sorting system **100** configured in accordance with various embodiments of the present disclosure to automatically classify/sort materials. A conveyor system **103** may be implemented to convey individual material pieces **101** through the sorting system **100** so that each of the individual material pieces **101** can be tracked, classified, and/or sorted into predetermined desired groups. Such a conveyor system **103** may be implemented with one or more conveyor belts on which the material pieces **101** travel, typically at a predetermined constant speed. However, certain embodiments of the present disclosure may be implemented with other types of conveyor systems as disclosed herein. Hereinafter, wherein applicable, the conveyor system **103** may also be referred to as the conveyor belt **103**. In one or more embodiments, some or all of the acts of conveying, stimulating, detecting, classifying, and sorting may be performed automatically, i.e., without human intervention. For example, in the system **100**, one or more sources of stimuli, one or more emissions detectors, a classification module, a sorting apparatus, and/or other system components may be configured to perform these and other operations automatically.

Furthermore, though the illustration in FIG. **1** depicts a single stream of material pieces **101** on a conveyor belt **103**, embodiments of the present disclosure may be implemented in which a plurality of such streams of material pieces are passing by the various components of the sorting system **100** in parallel with each other, or a collection of material pieces deposited in a random manner onto a conveyor system (e.g., the conveyor belt **103**) are passed by the various components of the system **100**. As such, certain embodiments of the present disclosure are capable of simultaneously tracking, classifying, and/or sorting a plurality of such parallel travelling streams of material pieces, or material pieces randomly deposited onto a conveyor system (belt). However, in accordance with embodiments of the present disclosure, singulation of the material pieces **101** is not required to track, classify, and/or sort the material pieces.

The conveyor belt **103** may be a conventional endless belt conveyor employing a conventional drive motor **104** suitable to move the conveyor belt **103** at the predetermined speeds. In accordance with certain embodiments of the present disclosure, some sort of suitable feeder mechanism may be utilized to feed the material pieces **101** onto the conveyor belt **103**, whereby the conveyor belt **103** conveys the material pieces **101** past various components within the sorting system **100**. Within certain embodiments of the present disclosure, the conveyor belt **103** is operated to travel at a predetermined speed by a conveyor belt motor **104**. This predetermined speed may be programmable and/or adjustable by the operator in any well-known manner. Within certain embodiments of the present disclosure, control of the conveyor belt motor **104** and/or the position detector **105** may be performed by an automation control system **108**. Such an automation control system **108** may be operated under the control of a computer system **107** and/or the functions for performing the automation control may be implemented in software within the computer system **107**.

A position detector **105**, which may be a conventional encoder, may be operatively coupled **5** to the conveyor belt **103** and the automation control system **108** to provide information corresponding to the movement (e.g., speed) of the conveyor belt **103**. Thus, as will be further described herein, through the utilization of the controls to the conveyor belt drive motor **104** and/or the automation control system **108** (and alternatively including the position detector **105**), as each of the material pieces **101** travelling on the conveyor belt **103** are identified, they can be tracked by location and time (relative to the system **100**) so that the various components of the sorting system **100** can be activated/deactivated as each material piece **101** passes within their vicinity. As a result, the automation control system **108** is able to track the location of each of the material pieces **101** while they travel along the conveyor belt **103**.

In accordance with certain embodiments of the present disclosure, after the material pieces **101** are received by the conveyor belt **103**, a tumbler and/or a vibrator may be utilized to separate the individual material pieces from a collection of material pieces, and then they may be positioned into one or more singulated (i.e., single file) streams. In accordance with alternative embodiments of the present disclosure, the material pieces may be positioned into one or more singulated (i.e., single file) streams, which may be performed by an active or passive singulator **106**. An example of a passive singulator is further described in U.S. Pat. No. 10,207,296. As previously discussed, incorporation or use of a singulator is not required. Instead, the conveyor system (e.g., the conveyor belt **103**) may simply convey a collection of material pieces, which have been deposited onto the conveyor belt **103** in a random manner.

Referring again to FIG. **1**, certain embodiments of the present disclosure may utilize a vision, or optical recognition, system **110** and/or a distance measuring device **111** as a means to begin tracking each of the material pieces **101** as they travel on the conveyor belt **103**. The vision system **110** may utilize one or more still or live action cameras **109** to note the position (i.e., location and timing) of each of the material pieces **101** on the moving conveyor belt **103**. The vision system **110** may be further, or alternatively, configured to perform certain types of identification (e.g., classification) of all or a portion of the material pieces **101**. For example, such a vision system **110** may be utilized to acquire information about each of the material pieces **101**. For example, the vision system **110** may be configured (e.g., with a machine learning system) to collect any type of information that can be utilized within the system **100** to selectively sort the material pieces **101** as a function of a set of one or more (user-defined) physical characteristics, including, but not limited to, color, hue, size, shape, texture, overall physical appearance, uniformity, composition, and/or manufacturing type of the material pieces **101**. The vision system **110** captures images of each of the material pieces **101** (including one-dimensional, two-dimensional, three-dimensional, or holographic imaging), for example, by using an optical sensor as utilized in typical digital cameras and video equipment. Such images captured by the optical sensor are then stored in a memory device as image data. In accordance with embodiments of the present disclosure, such image data represents images captured within optical wavelengths of light (i.e., the wavelengths of light that are observable by the typical human eye). However, alternative embodiments of the present disclosure may utilize sensors that are able to capture an image of a material made up of wavelengths of light outside of the visual wavelengths of the typical human eye.

In accordance with certain embodiments of the present disclosure, a sorting system may be implemented with one or more sensor systems **120**, which may be utilized solely or in combination with the vision system **110** to classify/identify material pieces **101**. A sensor system **120** may be configured with any type of sensor technology, including sensors utilizing irradiated or reflected electromagnetic radiation (e.g., utilizing infrared ("IR"), Fourier Transform IR ("FTIR"), Forward-looking Infrared ("FLIR"), Very Near Infrared ("VNIR"), Near Infrared ("NIR"), Short Wavelength Infrared ("SWIR"), Long Wavelength Infrared ("LWIR"), Medium Wavelength Infrared ("MWIR"), X-Ray Transmission ("XRT"), Gamma Ray, Ultraviolet, X-Ray Fluorescence ("XRF"), Laser Induced Breakdown Spectroscopy ("LIBS"), Raman Spectroscopy, Anti-stokes Raman Spectroscopy, Gamma Spectroscopy, Hyperspectral Spectroscopy (e.g., any range beyond visible wavelengths), Acoustic Spectroscopy, NMR Spectroscopy, Microwave Spectroscopy, Terahertz Spectroscopy, including one-dimensional, two-dimensional, or three-dimensional imaging with any of the foregoing), or by any other type of sensor technology, including but not limited to, chemical or radioactive. Implementation of an XRF system (e.g., for use as a sensor system **120** herein) is further described in U.S. Pat. No. 10,207,296.

It should be noted that though FIG. **1** is illustrated with a combination of a vision system **110** and a sensor system **120**, embodiments of the present disclosure may be implemented with any combination of sensor systems utilizing any of the sensor technologies disclosed herein, or any other sensor technologies currently available or developed in the future. Though FIG. **1** is illustrated as including a sensor system **120**, implementation of such a sensor system is optional within certain embodiments of the present disclosure. Within certain embodiments of the present disclosure, a combination of both the vision system **110** and one or more sensor systems **120** may be used to classify the material pieces **101**. Within certain embodiments of the present disclosure, any combination of one or more of the different sensor technologies disclosed herein may be used to classify the material pieces **101** without utilization of a vision system **110**. Furthermore, embodiments of the present disclosure may include any combinations of one or more sensor systems and/or vision systems in which the outputs of such sensor and/or vision systems are utilized by a machine learning system (as further disclosed herein) in order to classify/identify materials from a heterogeneous mixture of materials, which can then be sorted from each other.

In accordance with alternative embodiments of the present disclosure, a vision system **110** and/or sensor system(s) may be configured to identify which of the material pieces **101** are not of the kind to be sorted by the system **100** (sometimes referred to as contaminants), and send a signal to reject such material pieces. In such a configuration, the identified material pieces **101** may be diverted/ejected utilizing one of the mechanisms as described hereinafter for physically moving sorted material pieces into individual bins.

Within certain embodiments of the present disclosure, the distance measuring device **111** and accompanying control system **112** may be utilized and configured to measure the sizes and/or shapes of each of the material pieces **101** as they pass within proximity of the distance measuring device **111**, along with the position (i.e., location and timing) of each of the material pieces **101** on the moving conveyor belt **103**. An exemplary operation of such a distance measuring device **111** and control system **112** is further described in U.S. Pat. No. 10,207,296. Alternatively, as previously disclosed, the vision system **110** may be utilized to track the position (i.e., location and timing) of each of the material pieces **101** on the moving conveyor belt **103**.

Such a distance measuring device **111** may be implemented with a well-known visible light (e.g., laser light) system, which continuously measures a distance the light travels before being reflected back into a detector of the laser light system. As such, as each of the material pieces **101** passes within proximity of the device **111**, it outputs a signal to the control system **112** indicating such distance measurements. Therefore, such a signal may substantially represent an intermittent series of pulses whereby the baseline of the signal is produced as a result of a measurement of the distance between the distance measuring device **111** and the conveyor belt **103** during those moments when a material piece **101** is not in the proximity of the device **111**, while each pulse provides a measurement of the distance between the distance measuring device **111** and a material piece **101** passing by on the conveyor belt **103**. Since the material pieces **101** may have irregular shapes, such a pulse signal may also occasionally have an irregular height. Nevertheless, each pulse signal generated by the distance measuring device **111** provides the height of portions of each of the material pieces **101** as they pass by on the conveyor belt **103**. The length of each of such pulses also provides a measurement of a length of each of the material pieces **101** measured along a line substantially parallel to the direction of travel of the conveyor belt **103**. It is this length measurement (and alternatively the height measurements) that may be utilized within certain embodiments of the present disclosure to determine when to activate and deactivate the acquisition of detected fluorescence (i.e., the XRF spectrum) of each of the material pieces **101** by a sensor system **120** implementing an XRF system so that the detected fluorescence is obtained substantially only from each of the material pieces and not from any background surfaces, such as a conveyor belt **103**. This results in a more accurate detection and analysis of the fluorescence, and also saves time in the signal processing of the detected signals since only data associated with detected fluorescence from the material pieces is having to be processed.

Within certain embodiments of the present disclosure that implement sensor system(s) **120**, the sensor system(s) **120** may be configured to assist the vision system **110** to identify the composition, or relative compositions, and/or manufacturing types, of each of the material pieces **101** as they pass within proximity of the sensor system(s) **120**. The sensor system(s) **120** may include an energy emitting source **121**, which may be powered by a power supply **122**, for example, in order to stimulate a response from each of the material pieces **101**.

Within certain embodiments of the present disclosure, as each material piece **101** passes within proximity to the emitting source **121**, the sensor system **120** may emit an appropriate sensing signal towards the material piece **101**. One or more detectors **124** may be positioned and configured to sense/detect one or more physical characteristics from the material piece **101** in a form appropriate for the type of utilized sensor technology. The one or more detectors **124** and the associated detector electronics **125** capture this received sensed characteristics to perform signal processing thereon and produce digitized information representing the sensed characteristics, which is then analyzed in accordance with certain embodiments of the present disclosure, which may be used in order to assist the vision system **110** to classify each of the material pieces **101**. This classification, which may be performed within the computer system **107**, may then be utilized by the automation control system **108** to activate one of the N (N≥1) sorting devices **126** . . . **129** for sorting (e.g., diverting/ejecting) the material pieces **101** into one or more N (N≥1) sorting bins **136** . . . **139** according to the determined classifications. Four sorting devices **126** . . . **129** and four sorting bins **136** . . . **139** associated with the sorting devices are illustrated in FIG. **1** as merely a non-limiting example.

The sorting devices may include any well-known mechanisms for redirecting selected material pieces **101** towards a desired location, including, but not limited to, diverting the material pieces **101** from the conveyor belt system into the plurality of sorting bins. For example, a sorting device may utilize air jets, with each of the air jets assigned to one or more of the classifications. When one of the air jets (e.g., **127**) receives a signal from the automation control system **108**, that air jet emits a stream of air that causes a material piece **101** to be diverted/ejected from the conveyor system **103** into a sorting bin (e.g., **137**) corresponding to that air jet. High speed air valves from Mac Industries may be used, for example, to supply the air jets with an appropriate air pressure configured to divert/eject the material pieces **101** from the conveyor system **103**.

Although the example illustrated in FIG. **1** uses air jets to divert/eject material pieces, other mechanisms may be used to divert/eject the material pieces, such as robotically removing the material pieces from the conveyor belt, pushing the material pieces from the conveyor belt (e.g., with paint brush type plungers), causing an opening (e.g., a trap door) in the conveyor system **103** from which a material piece may drop, or using air jets to separate the material pieces into separate bins as they fall from the edge of the conveyor belt. A pusher device, as that term is used herein, may refer to any form of device which may be activated to dynamically displace an object on or from a conveyor system/device, employing pneumatic, mechanical, or other means to do so, such as any appropriate type of mechanical pushing mechanism (e.g., an

ACME screw drive), pneumatic pushing mechanism, or air jet pushing mechanism. Some embodiments may include multiple pusher devices located at different locations and/or with different diversion path orientations along the path of the conveyor system. In various different implementations, these sorting systems describe herein may determine which pusher device to activate (if any) depending on characteristics of material pieces identified by the machine learning system. Moreover, the determination of which pusher device to activate may be based on the detected presence and/or characteristics of other objects that may also be within the diversion path of a pusher device concurrently with a target item. Furthermore, even for facilities where singulation along the conveyor system is not perfect, the disclosed sorting systems can recognize when multiple objects are not well singulated, and dynamically select from a plurality of pusher devices which should be activated based on which pusher device provides the best diversion path for potentially separating objects within close proximity. In some embodiments, objects identified as target objects may represent material that should be diverted off of the conveyor system. In other embodiments, objects identified as target objects represent material that should be allowed to remain on the conveyor system so that non-target materials are instead diverted.

In addition to the N sorting bins **136** . . . **139** into which material pieces **101** are diverted/ejected, the system **100** may also include a receptacle or bin **140** that receives material pieces **101** not diverted/ejected from the conveyor system **103** into any of the aforementioned sorting bins **136** . . . **139**. For example, a material piece **101** may not be diverted/ejected from the conveyor system **103** into one of the N sorting bins **136** . . . **139** when the classification of the material piece **101** is not determined (or simply because the sorting devices failed to adequately divert/eject a piece), or when the material piece **101** contains a contaminant detected by the vision system **110** and/or the sensor system **120**. Thus, the bin **140** may serve as a default receptacle into which unclassified material pieces are dumped. Alternatively, the bin **140** may be used to receive one or more classifications of material pieces that have deliberately not been assigned to any of the N sorting bins **136** . . . **139**. These such material pieces may then be further sorted in accordance with other characteristics and/or by another sorting system.

Depending upon the variety of classifications of material pieces desired, multiple classifications may be mapped to a single sorting device and associated sorting bin. In other words, there need not be a one-to-one correlation between classifications and sorting bins. For example, it may be desired by the user to sort certain classifications of materials into the same sorting bin. To accomplish this sort, when a material piece **101** is classified as falling into a predetermined grouping of classifications, the same sorting device may be activated to sort these into the same sorting bin. Such combination sorting may be applied to produce any desired combination of sorted material pieces. The mapping of classifications may be programmed by the user (e.g., using the sorting algorithm (e.g., see FIG. **9**) operated by the computer system **107**) to produce such desired combinations. Additionally, the classifications of material pieces are user-definable, and not limited to any particular known classifications of material pieces.

The conveyor system **103** may include a circular conveyor (not shown) so that unclassified material pieces are returned to the beginning of the system **100** and run through the system **100** again. Moreover, because the system **100** is able to specifically track each material piece **101** as it travels on the conveyor system **103**, some sort of sorting device (e.g., the sorting device **129**) may be implemented to direct/eject a material piece **101** that the system **100** has failed to classify after a predetermined number of cycles through the system **100** (or the material piece **101** is collected in bin **140**).

Within certain embodiments of the present disclosure, the conveyor system **103** may be divided into multiple belts configured in series such as, for example, two belts, where a first belt conveys the material pieces past the vision system **110** and/or an implemented sensor system **120**, and a second belt conveys the material pieces from the vision system **110** and/or an implemented sensor system **120** to the sorting devices. Moreover, such a second conveyor belt may be at a lower height than the first conveyor belt, such that the material pieces fall from the first belt onto the second belt.

Within certain embodiments of the present disclosure that implement a sensor system **120**, the emitting source **121** may be located above the detection area (i.e., above the conveyor system **103**); however, certain embodiments of the present disclosure may locate the emitting source **121** and/or detectors **124** in other positions that still produce acceptable sensed/detected physical characteristics.

With systems **100** implementing an XRF system for a sensor system **120**, signals representing the detected XRF spectrum may be converted into a discrete energy histogram such as on a per-channel (i.e., element) basis, as further described herein. Such a conversion process may be implemented within the control system **123**, or the computer system **107**. Within certain embodiments of the present disclosure, such a control system **123** or computer system **107** may include a commercially available spectrum acquisition module, such as the commercially available Amptech MCA 5000 acquisition card and software programmed to operate the card. Such a spectrum acquisition module, or other software implemented within the system **100**, may be configured to implement a plurality of channels for dispersing x-rays into a discrete energy spectrum (i.e., histogram) with such a plurality of energy levels, whereby each energy level corresponds to an element that the system **100** has been configured to detect. The system **100** may be configured so that there are sufficient channels corresponding to certain elements within the chemical periodic table, which are important for distinguishing between different materials. The energy counts for each energy level may be stored in a separate collection storage register. The computer system **107** then reads each collection register to determine the number of counts for each energy level during the collection interval, and build the energy histogram. As will be described in more detail herein, a sorting algorithm configured in accordance with certain embodiments of the present disclosure may then utilize this collected histogram of energy levels to classify at least certain ones of the material pieces **101** and/or assist the vision system **110** in classifying the material pieces **101**.

In accordance with certain embodiments of the present disclosure that implement an XRF system as the sensor system **120**, the source **121** may include an in-line x-ray fluorescence ("IL-XRF") tube, such as further described within U.S. Pat. No. 10,207,296. Such an IL-XRF tube may include a separate x-ray source each dedicated for one or more streams (e.g., singulated) of conveyed material pieces. In such a case, the one or more detectors **124** may be implemented as XRF detectors to detect fluoresced x-rays from material pieces **101** within each of the singulated streams. Examples of such XRF detectors are further described within U.S. Pat. No. 10,207,296.

It should be appreciated that, although the systems and methods described herein are described primarily in relation to classifying material pieces in solid state, the disclosure is not so limited. The systems and methods described herein may be applied to classifying a material having any of a range of physical states, including, but not limited to a liquid, molten, gaseous, or powdered solid state, another state, and any suitable combination thereof.

The systems and methods described herein may be applied to classify and/or sort individual material pieces having any of a variety of sizes as small as a ¼ inch in diameter or less. Even though the systems and methods described herein are described primarily in relation to sorting individual material pieces of a singulated stream one at a time, the systems and methods described herein are not limited thereto. Such systems and methods may be used to stimulate and/or detect emissions from a plurality of materials concurrently. For example, as opposed to a singulated stream of materials being conveyed along one or more conveyor belts in series, multiple singulated streams may be conveyed in parallel. Each stream may be a on a same belt or on different belts arranged in parallel. Further, pieces may be randomly distributed on (e.g., across and along) one or more conveyor belts. Accordingly, the systems and methods described herein may be used to stimulate, and/or detect emissions from, a plurality of these small pieces at the same time. In other words, a plurality of small pieces may be treated as a single piece as opposed to each small piece being considered individually. Accordingly, the plurality of small pieces of material may be classified and sorted (e.g., diverted/ejected from the conveyor system) together. It should be appreciated that a plurality of larger material pieces also may be treated as a single material piece.

As previously noted, certain embodiments of the present disclosure may implement one or more vision systems (e.g., vision system **110**) in order to identify, track, and/or classify material pieces. In accordance with embodiments of the present disclosure, such a vision system(s) may operate alone to identify and/or classify and sort material pieces, or may operate in combination with a sensor system (e.g., sensor system **120**) to identify and/or classify and sort material pieces. If a sorting system (e.g., system **100**) is configured to operate solely with such a vision system(s) **110**, then the sensor system **120** may be omitted from the system **100** (or simply deactivated).

Such a vision system may be configured with one or more devices for capturing or acquiring images of the material pieces as they pass by on a conveyor system. The devices may be configured to capture or acquire any desired range of wavelengths irradiated or reflected by the material pieces, including, but not limited to, visible, infrared ("IR"), ultraviolet ("UV") light. For example, the vision system may be configured with one or more cameras (still and/or video, either of which may be configured to capture two-dimensional, three-dimensional, and/or holographical images) positioned in proximity (e.g., above) the conveyor system so that images of the material pieces are captured as they pass by the sensor system(s). In accordance with alternative embodiments of the present disclosure, data captured by a sensor system **120** may be processed (converted) into data to be utilized (either solely or in combination with the image data captured by the vision system **110**) for classifying/sorting of the material pieces. Such an implementation may be in lieu of, or in combination with, utilizing the sensor system **120** for classifying material pieces.

Regardless of the type(s) of sensed characteristics/information captured of the material pieces, the information may then be sent to a computer system (e.g., computer system **107**) to be processed by a machine learning system in order to identify and/or classify each of the material pieces. Such a machine learning system may implement any well-known machine learning system, including one that implements a neural network (e.g., artificial neural network, deep neural network, convolutional neural network, recurrent neural network, autoencoders, reinforcement learning, etc.), supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning, self learning, feature learning, sparse dictionary learning, anomaly detection, robot learning, association rule learning, fuzzy logic, artificial intelligence ("AI"), deep learning algorithms, deep structured learning hierarchical learning algorithms, support vector machine ("SVM") (e.g., linear SVM, nonlinear SVM, SVM regression, etc.), decision tree learning (e.g., classification and regression tree ("CART"), ensemble methods (e.g., ensemble learning, Random Forests, Bagging and Pasting, Patches and Subspaces, Boosting, Stacking, etc.), dimensionality reduction (e.g., Projection, Manifold Learning, Principal Components Analysis, etc.) and/or deep machine learning algorithms, such as those described in and publicly available at the deeplearning.net website (including all software, publications, and hyperlinks to available software referenced within this website), which is hereby incorporated by reference herein. Non-limiting examples of publicly available machine learning software and libraries that could be utilized within embodiments of the present disclosure include Python, OpenCV, Inception, Theano, Torch, PyTorch, Pylearn2, Numpy, Blocks, TensorFlow, MXNet, Caffe, Lasagne, Keras, Chainer, Matlab Deep Learning, CNTK, MatConvNet (a MATLAB toolbox implementing convolutional neural networks for computer vision applications), DeepLearnToolbox (a Matlab toolbox for Deep Learning (from Rasmus Berg Palm)), BigDL, Cuda-Convnet (a fast C++/CUDA implementation of convolutional (or more generally, feed-forward) neural networks), Deep Belief Networks, RNNLM, RNNLIB-RNNLIB, matrbm, deeplearning4j, Eblearn.lsh, deepmat, MShadow, Matplotlib, SciPy, CXXNET, Nengo-Nengo, Eblearn, cudamat, Gnumpy, 3-way factored RBM and mcRBM, mPOT (Python code using CUDAMat and Gnumpy to train models of natural images), ConvNet, Elektronn, OpenNN, NeuralDesigner, Theano Generalized Hebbian Learning, Apache Singa, Lightnet, and SimpleDNN.

Machine learning often occurs in two stages. For example, first, training occurs, which may be performed offline in that the system **100** is not being utilized to perform actual classifying/sorting of material pieces. The system **100** may be utilized to train the machine learning system in that homogenous sets (also referred to herein as control samples) of material pieces (i.e., having the same types or classes of materials) are passed through the system **100** (e.g., by a conveyor system **103**); and all such material pieces may not be sorted, but may be collected in a common bin (e.g., bin **140**). Alternatively, the training may be performed at another location remote from the system **100**, including using some other mechanism for collecting sensed information (characteristics) of homogenous sets of material pieces. During this training stage, algorithms within the machine learning system extract features from the captured information (e.g., using image processing techniques well known in the art). Non-limiting examples of training algorithms include, but are not limited to, linear regression, gradient descent, feed forward, polynomial regression, learning curves, regularized learning models, and logistic regression. It is during this training stage that the algorithms within the machine learning system learn the relationships between different types of materials and their features/characteristics (e.g., as captured by the vision system and/or sensor system(s)), creating a knowledge base for later classification of a heterogeneous mixture of material pieces received by the system **100** for sorting by desired classifications. Such a knowledge base may include one or more libraries, wherein each library includes parameters (also referred to herein as "neural network parameters") for utilization by the machine learning system in classifying material pieces. For example, one particular library may include parameters configured by the training stage to recognize and classify a particular type or class of material. In accordance with certain embodiments of the present disclosure, such libraries may be inputted into the machine learning system and then the user of the system **100** may be able to adjust certain ones of the parameters in order to adjust an operation of the system **100** (for example, adjusting the threshold effectiveness of how well the machine learning system recognizes a particular material from a heterogeneous mixture of materials).

Additionally, the inclusion of certain materials (e.g., chemical elements or compounds) in material pieces (e.g., metal alloys), or combinations of certain chemical elements or compounds, result in identifiable physical features (e.g., visually discernible characteristics) in materials, As a result, when a plurality of material pieces containing such a particular composition are passed through the aforementioned training stage, the machine learning system can learn how to distinguish such material pieces from others. Consequently, a machine learning system configured in accordance with certain embodiments of the present disclosure may be configured to sort between material pieces as a function of their respective material/chemical compositions. For example, such a machine learning system may be configured so that aluminum alloys can be sorted as a function of the percentage of a specified alloying material contained within the aluminum alloys.

For example, FIG. **6** shows captured or acquired images of exemplary material pieces of cast aluminum, which may be used during the aforementioned training stage. FIG. **7** shows captured or acquired images of exemplary material pieces of extruded aluminum, which may be used during the aforementioned training stage. FIG. **8** shows captured or acquired images of exemplary material pieces of wrought aluminum, which may be used during the aforementioned training stage. During the training stage, a plurality of material pieces of a particular (homogenous) classification (type) of material, which are the control samples, may be delivered past the vision system by the conveyor system so that the machine learning system detects, extracts, and learns what features visually represent such exemplary material pieces. In other words, images of cast aluminum material pieces such as shown in FIG. **6** may be first passed through such a training stage so that the machine learning algorithm "learns" how to detect, recognize, and classify material pieces composed of cast aluminum alloys. This creates a library of parameters particular to cast aluminum material pieces. Then, the same process can be performed with respect to images of extruded aluminum material pieces, such as shown in FIG. **7**, creating a library of parameters particular to extruded aluminum material pieces. And, the same process can be performed with respect to images of wrought aluminum material pieces, such as shown in FIG. **8**, creating a library of parameters particular to wrought aluminum material pieces. For each type of material to be classified by the vision system, any number of exemplary material pieces of that type of material may be passed by the vision system. Given a captured image as input data, the machine learning algorithms may use N classifiers, each of which test for one of N different material types.

After the algorithms have been established and the machine learning system has sufficiently learned the differences for the material classifications (e.g., within a user-defined level of statistical confidence), the libraries of neural network parameters for the different materials are then implemented into a material classifying and/or sorting system (e.g., system **100**) to be used for identifying and/or classifying material pieces from a heterogeneous mixture of material pieces, and then possibly sorting such classified material pieces if sorting is to be performed.

Techniques to construct, optimize, and utilize a machine learning system are known to those of ordinary skill in the art as found in relevant literature. Examples of such literature include the publications: Krizhevsky et al., "*ImageNet Classification with Deep Convolutional Networks*," Proceedings of the 25th International Conference on Neural Information Processing Systems, Dec. 3-6, 2012, Lake Tahoe, Nev., and LeCun et al., "*Gradient-Based Learning Applied to Document Recognition*," Proceedings of the IEEE, Institute of Electrical and Electronic Engineers (IEEE), November 1998, both of which are hereby incorporated by reference herein in their entirety.

In an example technique, data captured by a sensor and/or vision system with respect to a particular material piece may be processed as an array of data values. For example, the data may be image data captured by a digital camera or other type of imaging sensor with respect to a particular material piece and processed as an array of pixel values. Each data value may be represented by a single number, or as a series of numbers representing values. These values are multiplied by the neuron weight parameters, and may possibly have a bias added. This is fed into a neuron nonlinearity. The resulting number output by the neuron can be treated much as the values were, with this output multiplied by subsequent neuron weight values, a bias optionally added, and once again fed into a neuron nonlinearity. Each such iteration of the process is known as a "layer" of the neural network. The final outputs of the final layer may be interpreted as probabilities that a material is present or absent in the captured data pertaining to the material piece. Examples of such a process are described in detail in both of the previously noted "*ImageNet Classification with Deep Convolutional Networks*" and "*Gradient-Based Learning Applied to Document Recognition*" references.

In accordance with embodiments of the present disclosure, as a final layer (the "classification layer"), the final set of neurons' outputs is trained to represent the likelihood a material piece is associated with the captured data. During operation, if the likelihood that a material piece is associated with the captured data is over a user-specified threshold, then it is determined that the particular material piece is indeed associated with the captured data. These techniques can be extended to determine not only the presence of a type of material associated with particular captured data, but also whether sub-regions of the particular captured data belong to one type of material or another type of material. This process is known as segmentation, and techniques to use neural networks exist in the literature, such as those known as "fully convolutional" neural networks, or networks that otherwise include a convolutional portion (i.e., are partially convolutional), if not fully convolutional. This allows for material location and size to be determined.

It should be understood that the present disclosure is not exclusively limited to machine learning techniques. Other common techniques for material classification/identification may also be used. For instance, a sensor system may utilize optical spectrometric techniques using multi- or hyper-spectral cameras to provide a signal that may indicate the presence or absence of a type of material by examining the spectral emissions of the material. Photographs of a material piece may also be used in a template-matching algorithm, wherein a database of images is compared against an acquired image to find the presence or absence of certain types of materials from that database. A histogram of the captured image may also be compared against a database of histograms. Similarly, a bag of words model may be used with a feature extraction technique, such as scale-invariant feature transform ("SIFT"), to compare extracted features between a captured image and those in a database.

Therefore, as disclosed herein, certain embodiments of the present disclosure provide for the identification/classification of one or more different materials in order to determine which material pieces should be diverted from a conveyor system or device. In accordance with certain embodiments, machine learning techniques are utilized to train (i.e., configure) a neural network to identify a variety of one or more different materials. Images, or other types of sensed information, are captured of materials (e.g., traveling on a conveyor system), and based on the identification/classification of such materials, the systems described herein can decide which material piece should be allowed to remain on the conveyor system, and which should be diverted/removed from the conveyor system (for example, either into a collection bin, or diverted onto another conveyor system).

In accordance with certain embodiments of the present disclosure, a machine learning system for an existing installation may be dynamically reconfigured to detect and recognize characteristics of a new material by replacing a current set of neural network parameters with a new set of neural network parameters.

One point of mention here is that, in accordance with certain embodiments of the present disclosure, the detected/extracted features/characteristics of the material pieces may not be necessarily simply particularly identifiable physical characteristics; they can be abstract formulations that can only be expressed mathematically, or not mathematically at all; nevertheless, the machine learning system parses all of the data to look for patterns that allow the control samples to be classified during the training stage. Furthermore, the machine learning system may take subsections of captured information of a material piece and attempt to find correlations between the pre-defined classifications.

In accordance with certain embodiments of the present disclosure, instead of utilizing a training stage whereby control samples of material pieces are passed by the vision system and/or sensor system(s), training of the machine learning system may be performed utilizing a labeling/annotation technique (or any other supervised learning technique) whereby as data/information of material pieces are captured by a vision/sensor system, a user inputs a label or annotation that identifies each material piece, which is then used to create the library for use by the machine learning system when classifying material pieces within a heterogenous mixture of material pieces.

In accordance with certain embodiments of the present disclosure, any sensed characteristics output by any of the sensor systems **120** disclosed herein may be input into a machine learning system in order to classify and/or sort materials. For example, in a machine learning system implementing supervised learning, sensor system **120** outputs that uniquely characterize a particular type or composition of material (e.g., a particular metal alloy) may be used to train the machine learning system.

As previously disclosed herein, though x-ray transmission technology can be used to sort between some cast, extruded, and/or wrought aluminum alloys, it does not classify all of the cast and/or extruded alloys correctly due to the large variance in their respective densities. The use of machine learning systems, however, does not use density to make the decision of whether the alloy is cast, extruded, or wrought, and therefore, does not suffer from this problem. Recent melt test results by the inventors show that machine learning systems as configured in accordance with embodiments of the present disclosure are >99% accurate in their ability to distinguish between cast, extruded, and/or wrought aluminum alloys (e.g., see FIGS. **4**-**5**). This accuracy is far greater than the x-ray transmission technology, and enables a cost-effective system and method for classifying/sorting between cast aluminum alloys, extruded aluminum alloys, and/or wrought aluminum alloys. As referenced herein, a melt test is when selected metal pieces are melted together, and a composition analysis is performed on the melted together pieces to determine the percentages of the various metals existing within the melt.

FIG. **2** illustrates a table listing chemical composition limits required for several common aluminum alloys utilized to manufacture various end products. Therefore, any satisfactory recycling process should be efficient and cost effective for producing end products that adhere to such chemical composition limits.

Lots of shredded aluminum scrap referred to in the industry as Twitch typically include a mixture of various aluminum scrap alloys from automobiles, construction/demolition projects, refrigerators, washing machines, some soda cans, and/or other appliances. This may include cast, extruded, and/or wrought aluminum alloys, and thus may contain significant amounts of Si, Mg, Fe, Mn, Cu, and Zn, and can vary significantly from lot to lot depending on the composition of scrap metals being shredded.

FIG. **3** illustrates a table listing data obtained from a melt test of a batch of Twitch. As can be seen from the composition of the melted Twitch that it contains a significantly high content of silicon, such that none of the wrought aluminum alloys such as 3105 or 6061 (e.g., see FIG. **2**) can be fabricated from the mixed scrap, because silicon cannot be removed from the molten aluminum. Thus, currently, typical shredded lots of Twitch can be merely melted to manufacture the lowest grade aluminum alloy (e.g., 380 series cast aluminum alloy, which can be used for engine block castings). However, as shown in FIG. **3**, a typical lot of Twitch contains a significant amount of magnesium, which needs to be significantly removed (e.g., to less than 1% of the composition, or even less than 0.5% in some situations) to obtain the 380 cast aluminum alloy composition. The current method of choice is bubbling chlorine gas through the molten Twitch to produce magnesium chloride, which can be removed as slag from the molten Twitch. However, chlorine is a toxic substance, and its removal by such methods results in extra costs associated with the process and the fact that it is toxic. Additionally, such a Mg/Cl process results in a loss of some of the aluminum.

After going through a shredder, sidings (typically made from thin aluminum sheets), extrusions (typically manufactured from thick aluminum framing bars), and castings look very different. FIG. **6** shows visual images of exemplary scrap pieces from cast aluminum. FIG. **7** shows visual images of exemplary scrap pieces from aluminum extrusions. FIG. **8** shows visual images of exemplary scrap pieces from wrought aluminum. Composition-wise, extruded aluminum has a similar composition as wrought aluminum (because of the relatively low amount (<1.5%) of silicon), while all types of cast aluminum will contain more than 5% silicon.

Embodiments of the present disclosure utilize a vision system as described herein capable of classifying/sorting between these three different types of aluminum scrap pieces. In doing so, the utilization of chlorine is not required, while resulting in recycled cast aluminum having less than 1% Mg in the final composition of the sorted scrap pieces (or ingots made from the sorted scrap pieces), and even less than 0.5% Mg.

Embodiments of the present disclosure are configured to sort the wrought aluminum alloy material pieces from the Twitch, which contains both wrought and cast aluminum pieces. In certain embodiments of the present disclosure, extruded aluminum alloy pieces can be sorted with the wrought aluminum alloy pieces (or sorted separately from both cast and wrought aluminum). Since most of the Mg is within the wrought aluminum, the remaining aluminum scrap pieces, containing mostly cast aluminum alloys, have relatively insignificant amounts of Mg. In accordance with certain embodiments of the present disclosure, another sort (or plurality of sorting cycles) can be performed on these remaining aluminum scrap pieces (also referred to herein as the "cast fraction") in order to classify/sort between any plurality of different cast aluminum alloys and/or to remove other impurities (e.g., scrap pieces composed of PCB, stainless steel, foam, rubber, etc.).

The cast fraction may include cast alloys such as 319, 356, 360, and/or 380 series alloy pieces. These alloys contain varying amounts of silicon, Cu, Zn, Fe, and Mn, but contain extremely small amounts of Mg, typically 0-0.6%. FIG. **4** illustrates a table listing an exemplary composition obtained from a melt test of cast fractions produced by sorting in accordance with embodiments of the present disclosure. As can be seen, the fraction of Mg is 0.08%, which is less than the previously stated goal of less than 1%.

FIG. **5** illustrates a table listing percentages of metals in a composition obtained from a melt test of wrought aluminum scrap pieces sorted from Twitch in accordance with embodiments of the present disclosure (also referred to herein as the "wrought fraction"). As is clear, the sorted wrought fraction can be used for fabricating any of the wrought alloys by adding small amounts of the required metals (for example, see FIG. **2**).

Furthermore, in accordance with embodiments of the present disclosure, the wrought fraction can be sorted again into sheet metal scrap and/or extrusion scrap fractions. These can be melted separately to manufacture either 3105, 5052, or 6061 alloys (e.g., see FIG. **2**). As shown by the examples in FIGS. **6-8**, aluminum extrusions have an overall physical appearance that is distinguishable from cast and wrought aluminum scrap pieces, which can be learned by a machine learning system configured in accordance with embodiments of the present disclosure.

In accordance with certain embodiments of the present disclosure, one or more of the sensor systems **120** disclosed herein may be utilized to classify/sort either or both of the aforementioned cast fractions and wrought fractions. For example, one or both of an XRF system and/or a sensor system using LIBs may be utilized to classify/sort between two or more different cast aluminum alloys. The utilization of an XRF system to do so is disclosed in U.S. Pat. No. 10,207,296. Moreover, such sensor systems may be configured to classify/sort between two or more different cast aluminum alloys within any heterogeneous mixture of materials without having to perform a previous classification/sort using a vision system with a machine learning system.

FIG. **9** illustrates a flowchart diagram depicting exemplary embodiments of a process **3500** of classifying/sorting material pieces utilizing a vision system and/or sensor system in accordance with certain embodiments of the present disclosure. The process **3500** may be configured to operate within any of the embodiments of the present disclosure described herein, including the system **100** of FIG. **1**. Operation of the process **3500** may be performed by hardware and/or software, including within a computer system (e.g., computer system **3400** of FIG. **14**) controlling the sorting system (e.g., the computer system **107**, the vision system **110**, and/or the sensor system(s) **120** of FIG. **1**). In the process block **3501**, the material pieces may be manipulated into one or more singulated streams onto a conveyor system. As previously disclosed, such singulation of the material pieces is optional. In the process block **3502**, the location on the conveyor system of each material piece is detected for tracking of each material piece as it travels through the sorting system. This may be performed by the vision system **110** (for example, by distinguishing a material piece from the underlying conveyor system material while in communication with a conveyor system position detector (e.g., the position detector **105**)). Alternatively, a linear sheet laser beam can be used to locate the pieces. Or, any system that can create a light source (including, but not limited to, visual light, UV, and IR) and have a detector that can be used to locate the pieces. In the process block **3503**, when a material piece has traveled in proximity to one or more of the vision system and/or the sensor system(s), sensed information/characteristics of the material piece is captured/acquired. In the process block **3504**, a vision system (e.g., implemented within the computer system **107**), such as previously disclosed, may perform pre-processing of the captured information, which may be utilized to detect (extract) each of the material pieces (e.g., from the background (e.g., the conveyor belt); in other words, the pre-processing may be utilized to identify the difference between the material piece and the background). Well-known image processing techniques such as dilation, thresholding, and contouring may be utilized to identify the material piece as being distinct from the background. In the process block **3505**, segmentation may be performed. For example, the captured information may include information pertaining to one or more material pieces. Additionally, a particular material piece may be located on a seam of the conveyor belt when its image is captured. Therefore, it may be desired in such instances to isolate the image of an individual material piece from the background of the image. In an exemplary technique for the process block **3505**, a first step is to apply a high contrast of the image; in this fashion, background pixels are reduced to substantially all black pixels, and at least some of the pixels pertaining to the material piece are brightened to substantially all white pixels. The image pixels of the material piece that are white are then dilated to cover the entire size of the material piece. After this step, the location of the material piece is a high contrast image of all white pixels on a black background. Then, a contouring algorithm can be utilized to detect boundaries of the material piece. The boundary information is saved, and the boundary locations are then transferred to the original image. Segmentation is then performed on the original image on an area greater than the boundary that was earlier defined. In this fashion, the material piece is identified and separated from the background.

In the optional process block **3506**, the material pieces may be conveyed along the conveyor system within proximity of a distance measuring device and/or a sensor system in order to determine a size and/or shape of the material pieces, which may be useful if an XRF system or some other spectroscopy sensor is also implemented within the sorting system. In the process block **3507**, post processing may be performed. Post processing may involve resizing the captured information/data to prepare it for use in the neural networks. This may also include modifying certain properties (e.g., enhancing image contrast, changing the image background, or applying filters) in a manner that will yield an enhancement to the capability of the machine learning system to classify the material pieces. In the process block **3509**, the data may be resized. Data resizing may be necessary under certain circumstances to match the data input requirements for certain machine learning systems, such as neural networks. For example, neural networks may require much smaller image sizes (e.g., 225×255 pixels or 299×299 pixels) than the sizes of the images captured by typical digital cameras. Moreover, the smaller the input data size, the less processing time is needed to perform the classification. Thus, smaller data sizes can ultimately increase the throughput of the sorter system **100** and increase its value.

In the process blocks **3510** and **3511**, for each material piece, the type or class of material is identified/classified based on the sensed/detected features. For example, the process block **3510** may be configured with a neural network employing one or more machine learning algorithms, which compare the extracted features with those stored in the knowledge base generated during the training stage, and assigns the classification with the highest match to each of the material pieces based on such a comparison. The algorithms of the machine learning system may process the captured information/data in a hierarchical manner by using automatically trained filters. The filter responses are then successfully combined in the next levels of the algorithms until a probability is obtained in the final step. In the process block **3511**, these probabilities may be used for each of the N classifications to decide into which of the N sorting bins the respective material pieces should be sorted. For example, each of the N classifications may be assigned to one sorting bin, and the material piece under consideration is sorted into that bin that corresponds to the classification returning the highest probability larger than a predefined threshold. Within embodiments of the present disclosure, such predefined thresholds may be preset by the user. A particular material piece may be sorted into an outlier bin (e.g., sorting bin **140**) if none of the probabilities is larger than the predetermined threshold.

Next, in the process block **3512**, a sorting device corresponding to the classification, or classifications, of the material piece is activated. Between the time at which the image of the material piece was captured and the time at which the sorting device is activated, the material piece has moved from the proximity of the vision system and/or sensor system(s) to a location downstream on the conveyor system (e.g., at the rate of conveying of a conveyor system). In embodiments of the present disclosure, the activation of the sorting device is timed such that as the material piece passes the sorting device mapped to the classification of the material piece, the sorting device is activated, and the material piece is diverted/ejected from the conveyor system into its associated sorting bin. Within embodiments of the present disclosure, the activation of a sorting device may be timed by a respective position detector that detects when a material piece is passing before the sorting device and sends a signal to enable the activation of the sorting device. In the process block **3513**, the sorting bin corresponding to the sorting device that was activated receives the diverted/ejected material piece.

FIG. **10** illustrates a flowchart diagram depicting exemplary embodiments of a process **400** of sorting material pieces in accordance with certain embodiments of the present disclosure. The process **400** may be configured to operate within any of the embodiments of the present disclosure described herein, including the system **100** of FIG. **1**. The process **400** may be configured to operate in conjunction with the process **3500**. For example, in accordance with certain embodiments of the present disclosure, the process blocks **403** and **404** may be incorporated in the process **3500** (e.g., operating in series or in parallel with the process blocks **3503**-**3510**) in order to combine the efforts of a vision system **110** that is implemented in conjunction with a machine learning system with a sensor system (e.g., the sensor system **120**) that is not implemented in conjunction with a machine learning system in order to classify and/or sort material pieces.

Operation of the process **400** may be performed by hardware and/or software, including within a computer system (e.g., computer system **3400** of FIG. **14**) controlling the sorting system (e.g., the computer system **107** of FIG. **1**). In the optional process block **401**, the material pieces may be manipulated into one or more singulated streams onto a conveyor system. Next, in the optional process block **402**, the material pieces may be conveyed along the conveyor system within proximity of a distance measuring device and/or an optical imaging system in order to determine a size and/or shape of the material pieces. In the process block **403**, when a material piece has traveled in proximity of the sensor system, the material piece may be interrogated, or stimulated, with EM energy (waves) or some other type of energy appropriate for the particular type of sensor technology utilized by the sensor system. In the process block **404**, physical characteristics of the material piece are sensed/detected by the sensor system. In the process block **405**, for at least some of the material pieces, the type of material is identified/classified based (at least in part) on the sensed/detected characteristics, which may be combined with the classification by the machine learning system in conjunction with the vision system **110**.

Next, if sorting of the material pieces is to be performed, in the process block **406**, a sorting device corresponding to the classification, or classifications, of the material piece is activated. Between the time at which the material piece was sensed and the time at which the sorting device is activated, the material piece has moved from the proximity of the sensor system to a location downstream on the conveyor system, at the rate of conveying of the conveyor system. In certain embodiments of the present disclosure, the activation of the sorting device is timed such that as the material piece passes the sorting device mapped to the classification of the material piece, the sorting device is activated, and the material piece is diverted/ejected from the conveyor system into its associated sorting bin. Within certain embodiments of the present disclosure, the activation of a sorting device may be timed by a respective position detector that detects when a material piece is passing before the sorting device and sends a signal to enable the activation of the sorting device. In the process block **407**, the sorting bin corresponding to the sorting device that was activated receives the diverted/ejected material piece.

In accordance with certain embodiments of the present disclosure, a plurality of at least a portion of the system **100** may be linked together in succession in order to perform multiple iterations or layers of sorting. For example, when two or more systems **100** are linked in such a manner, the conveyor system may be implemented with a single conveyor belt, or multiple conveyor belts, conveying the material pieces past a first vision system (and, in accordance with certain embodiments, a sensor system) configured for sorting material pieces of a first set of a heterogeneous mixture of materials by a sorter (e.g., the first automation control system **108** and associated one or more sorting devices **126** . . . **129**) into a first set of one or more receptacles (e.g., sorting bins **136** . . . **139**), and then conveying the material pieces past a second vision system (and, in accordance with certain embodiments, another sensor system) configured for sorting material pieces of a second set of a heterogeneous mixture of materials by a second sorter into a second set of one or more sorting bins.

Such successions of systems **100** can contain any number of such systems linked together in such a manner. In accordance with certain embodiments of the present disclosure, each successive vision system may be configured to sort out a different material than previous vision system(s).

Referring to FIG. **11**, there is illustrated a schematic diagram of a non-limiting example of a linking of successive sorting systems in a manner as previously described, which may be implemented with the sorting system **100**, or any similar sorting system utilizing one or more vision systems implementing a machine learning system (e.g., utilizing artificial intelligence ("AI") and/or one or more sensor systems **120**) (for the sake of simplicity, with respect to the following discussion of FIG. **11**, such combinations of one or more vision systems and/or one or more sensor systems will simply be referred to as a material classification system). In FIG. **11**, the various arrows schematically depict how the various material pieces are conveyed along such an exemplary sorting system. In this non-limiting example, four separate sorting systems are illustrated, though any number of such sorting systems may be combined in any manner in order to separate and sort various different classes of materials. The example in FIG. **11** describes various classes of materials to be sorted, but embodiments of the present disclosure are applicable to the sorting of any combination of a heterogeneous mixture of material pieces.

In this particular example, a group of materials that includes a heterogeneous mixture **3801***a* of aluminum, stainless steel, plastic, wood, rubber, brass, copper, PCB, e-scrap, and copper wire is deposited onto a first conveyor system **3803***a* (identified as Conveyor Belt #**1** in FIG. **11**), for example, from a ramp or chute **3802***a* (e.g., ramp or chute **102**). The conveyor system **3803***a* conveys the material pieces **3801***a* past a material classification system **3810***a*, which may be configured to classify/sort the material pieces made of stainless steel from the remainder of the material pieces (identified as Sort #**1**) utilizing the Sorter **3826***a*, which may utilize any of the sorting devices described herein, for deposit into a receptacle or bin **3836***a*.

The remaining heterogeneous mixture of material pieces **3801***b* may then be conveyed along the same conveyor system, or deposited **3802***b* onto a separate conveyor system **3803***b* (identified as Conveyor Belt #**2** in FIG. **11**). The conveyor system **3803***b* passes these material pieces **3801***b* past another material classification system **3810***b*, which may be configured to identify and sort the material pieces made of aluminum (identified as Sort #**2**) using the Sorter **3826***b* for depositing in a separate bin **3836***b* or other receptacle.

In this particular example, the remaining heterogeneous mixture of material pieces **3801***c* (i.e., minus the material pieces classified as stainless steel and aluminum material pieces) may then be deposited **3802***c* onto another conveyor system **3803***c* (identified as Conveyor Belt #**3** in FIG. **11**) for identification by the material classification system **3810***c* to be sorted by a Sorter **3826***c* (identified as Sort #**3**). This section of the sorting system may be configured to separate and sort material pieces made of copper, copper wire, and brass, which may be deposited into one or more bins. In accordance with certain embodiments of the present disclosure, each of the material pieces classified as copper, copper wire, and brass material pieces may be individually sorted and deposited into separate bins for copper **3836***c*, copper wire **3837***c*, and brass **3838***c*. The remaining heterogeneous mixture of material pieces (plastic wood, rubber, PCB, and e-scrap) may then be deposited into a receptacle or bin **3840**, or may be further processed by an additional sorting system (not shown) as previously described.

Embodiments of the present disclosure are not limited to a linear succession of such sorting systems, but may include a combination of branching of such sorting systems for further classification and sorting of a particular class or classes of materials. For example, FIG. **11** illustrates how the material pieces classified as aluminum alloy material pieces **3836***b* sorted in Sort #**2** may then be deposited **3802***d* onto another conveyor system **3803***d* (identified as Conveyor Belt #**4** in FIG. **11**). For example, the Sorter **3826***b* may physically sort such aluminum alloy material pieces onto another conveyor system, such as the conveyor system, or the receptacle **3836***b* in which the aluminum alloy material pieces have been deposited may be a ramp or chute for depositing the aluminum alloy material pieces onto the conveyor system, or the receptacle containing the aluminum alloy material pieces may simply be manipulated to deposit the aluminum alloy material pieces onto the conveyor system **3803***d*. A material classification system **3810***d* may then be configured to classify these aluminum alloy material pieces into cast aluminum alloys and wrought aluminum alloys (e.g., such as described herein with respect to FIGS. **6-8**). In this Sort #**4**, a Sorter **3826***d* may then be configured to separate the cast aluminum alloys from the wrought aluminum alloys based on the classification by the material classification system **3810***d* whereby the cast aluminum alloys may be deposited into a bin **3837***d* and the wrought aluminum alloys may be deposited into a bin **3836***d*.

A variation in the system of FIG. **11** may include a further classification/sort of the cast aluminum alloys into different predefined cast aluminum alloys using one or more sensor systems **120**, including, but not limited to, an XRF system such as described with respect to FIGS. **13**A-**13**B. And another variation in the system of FIG. **11** may include a further classification/sort of the wrought aluminum alloys into different predefined wrought aluminum alloys using one or more sensor systems **120**, including, but not limited to, an XRF system such as described with respect to FIGS. **13**A-**13**B.

As can be readily seen, the sorting system illustrated in FIG. **11** may be modified into any combination of sorting systems for sorting materials as desired.

In accordance with various embodiments of the present disclosure, different types or classes of materials may be classified by different types of sensors each for use with a machine learning system, and combined to classify material pieces in a stream of scrap or waste.

In accordance with various embodiments of the present disclosure, data from two or more sensors can be combined using a single or multiple machine learning systems to perform classifications of material pieces.

In accordance with various embodiments of the present disclosure, multiple sensor systems can be mounted onto a single conveyor system, with each sensor system utilizing a different machine learning system. In accordance with various embodiments of the present disclosure, multiple sensor systems can be mounted onto different conveyor systems, with each sensor system utilizing a different machine learning system.

Referring to FIGS. **12**A-**12**C, there is illustrated systems and processes configured in accordance with certain embodiments of the present disclosure in which materials (e.g., scrap) may be sorted for recycling. Referring to FIG. **12**A, materials, which may have been shredded, may be sorted between ferrous and non-ferrous materials. For example, a magnet may be utilized to remove the ferrous material pieces. The remaining non-ferrous materials may typically include non-ferrous metals (often referred to as Zorba) and other "junk" materials (e.g., cloth, leather, foam rubber, rubber, plastics, wood, PCBs, glass, etc.).

The Zorba may then be separated from the junk materials, for example, by utilization of a well-known eddy current method. The Zorba may include one or more of various metals (e.g., copper, brass, zinc, stainless steel, aluminum (cast and/or wrought alloys), lead, high-Z cast aluminum alloys (e.g., cast aluminum alloys 319 and 380), low-Z cast aluminum alloys (e.g., cast aluminum alloys 356 and 360), nickel alloys, and gold or silver (e.g., located within PCBs).

The Zorba may be sorted between heavier and lighter metals. This may be accomplished utilizing various separating or sorting technologies. For example, a heavy media (e.g., water made selectively dense with sand) may be utilized to separate the heavy metals (also referred to as Zebra or "Heavies") from the lighter metals (e.g., Twitch).

Alternatively, a machine learning system configured in accordance with embodiments of the present disclosure may be utilized to sort the Zorba into the separate groups of Zebra and Twitch. Furthermore, certain embodiments of the present disclosure may be configured to sort out PCBs and/or "meatballs" and airbag canisters from ferrous scrap streams.

In another alternative embodiment, such a machine learning system may be utilized to sort out wrought aluminum from the Zorba. Applicants have discovered that typical Zorba (e.g., from shredded vehicles) can contain about 20% by weight and 50%-60% by volume of wrought aluminum. The wrought aluminum may be sorted out from the Zorba utilizing such a machine learning system (which has been trained to recognize wrought aluminum material pieces) at a relatively very high throughput rate (e.g., the conveyor belt operating at 350-500 feet per minute), which can reduce the number of material pieces in the lot by almost 60% before proceeding to a next sorting step.

Whether Twitch or just wrought aluminum is separated/sorted out from the Zorba, a next process may be performed to sort various metals from the Zebra. As shown in FIG. **12**B, this may be performed using a machine learning system (e.g., utilizing artificial intelligence), an x-ray fluorescence ("XRF") system utilized within a sorting system (such as disclosed in U.S. Pat. No. 10,207,296, which is hereby incorporate by reference herein), or a combination of a machine learning system and an XRF system (e.g., by first sorting with the machine learning system and then with the XRF system). Alternatively, any other of the disclosed sensor systems **120** (e.g., LIBs, XRT, etc.) may be utilized instead of an XRF system. The Zebra may be sorted to separately extract various metals (e.g., copper zinc, brass, etc.). Referring to FIG. **12**C, the Twitch can be separated into heavy aluminum and lighter aluminum plus magnesium material pieces, for example, by utilizing a heavy media (e.g., made selectively dense with aluminum oxide). Note that since magnesium (e.g., cast magnesium) is less dense (thus lighter) than other metals, the Twitch may include material pieces composed of cast magnesium, such as for example, from electric lawn mower engines and electric power drills. Since magnesium is less dense than aluminum, a certain density of heavy media will float cast magnesium and sink cast aluminum. A problem is that wrought aluminum and foam aluminum may also float with the cast magnesium, since these forms of aluminum may have trapped air in pockets, which can result in too much magnesium with sorted wrought aluminum. However, since the wrought aluminum and magnesium have different appearances, a machine learning system as disclosed herein can be trained to sort between the materials.

As shown in FIG. **12**C, the light aluminum can be separated from the magnesium. Additionally, the heavy aluminum material pieces may be run through an AI sorter as described herein to separate cast aluminum from wrought aluminum within that grouping.

FIGS. **13**A-**13**B illustrate a system and process **1600** configured in accordance with certain embodiments of the present disclosure in order to sort a plurality of metal alloy pieces. FIG. **13**A illustrates an exemplary non-limiting schematic diagram of a side view of such a system and process **1600**, while FIG. **13**B illustrates a top view.

A plurality of metal alloy pieces **1601** may be conveyed (e.g., by a conveyor belt **1602**) to be picked up by an inclined conveyor system **1603**. Note that the material pieces **1601** are not depicted in FIG. **13**B for the sake of simplicity. The conveyor system **1603** conveys the material pieces **1601** past an XRF or AI system **1610** in order to classify the material pieces for sorting. Alternatively, any other of the disclosed sensor systems **120** (e.g., LIBs, XRT, etc.) may be utilized instead of an XRF system.

In a non-limiting example, an XRF or AI system **1610** may be configured to recognize and classify those material pieces composed of aluminum alloy(s). The conveyor system **1603** may be configured to operate at a sufficient speed in order to "throw" the material pieces classified as aluminum alloy(s) onto a following inclined conveyor system **1604**. Material pieces not classified as composed of aluminum alloy(s) are ejected by a sorting device **1620** onto a lower positioned conveyor system **1606**. For example, such a sorting device **1620** may be an air jet nozzle such as described herein, which is actuated to eject a material piece not classified as aluminum alloy(s) from the normal trajectory of material pieces being "thrown" from the end of the conveyor system **1603** onto the conveyor system **1604**. The material pieces not classified as aluminum alloy(s) may be conveyed into a bin or receptacle **1630**.

The material pieces classified as aluminum alloy(s) may be conveyed past an XRF or AI system **1611**, which may be configured to identify and classify those material pieces that are composed of wrought aluminum alloy(s). The conveyor system **1604** may be configured to operate at a sufficient speed in order to "throw" the material pieces not classified as wrought aluminum alloy(s) onto a following inclined conveyor system **1605**. Material pieces classified as composed of wrought aluminum alloy(s) may be ejected by a sorting device **1621** onto a lower positioned conveyor system **1607**. For example, such a sorting device **1621** may be an air jet nozzle such as described herein, which is actuated to eject a material piece classified as wrought aluminum alloy(s) from the normal trajectory of material pieces being "thrown" from the end of the conveyor system **1604** onto the conveyor system **1605**. The classified material pieces may be conveyed into a bin or receptacle **1631**.

The material pieces not classified as wrought aluminum alloy(s) may be primarily composed of cast aluminum alloys and may be conveyed past an XRF or AI system **1612**, which may be configured to identify and classify those material pieces that contain a threshold amount of a particular material in order to classify a particular cast aluminum alloy that is known to contain such a particular material. For example, various cast aluminum alloys can be sorted by an XRF system as described herein. Cast aluminum alloy 319 has a single large copper peak observable in its XRF spectrum, cast aluminum alloy 356 does not have such a large copper peak, and cast aluminum alloy 380 has both large copper and zinc peaks. These large differences can be utilized by an XRF system to sort between these cast aluminum alloys with high accuracy.

The conveyor system **1605** may be configured to operate at a sufficient speed in order to "throw" the material pieces classified as this particular cast aluminum alloy onto yet another conveyor system (not shown) or into a bin or receptacle **1633**. The material pieces classified as a different cast aluminum alloy may be ejected by a sorting device **1622** onto a lower positioned conveyor system **1608**. For example, such a sorting device **1622** may be an air jet nozzle such as described herein, which is actuated to eject a material piece classified as the other different cast aluminum alloy, for example, from the normal trajectory of material pieces being "thrown" from the end of the conveyor system **1605**. These classified material pieces may be conveyed into a bin or receptacle **1632**.

Note that the system and process **1600** is not limited to one line of conveyor systems, but may be expanded to multiple lines each ejecting classified material pieces onto multiple conveyor systems (e.g., conveyor systems **1606** . . . **1608**). Likewise, one or more of the conveyor systems **1606** . . . **1608** may be implemented with an additional XRF or AI system to further classify those material pieces. For example, the material pieces classified as composed of wrought aluminum alloys (and collected onto the conveyor system **1607**) may be conveyed past another XRF system (or other sensor system **120**) in order to classify and/or sort between one or more wrought aluminum alloys.

Therefore, in accordance with certain embodiments of the present disclosure, a classifying/sorting system and process can first sort out wrought aluminum material pieces, then the remaining material pieces can be run through a classifying/sorting system implementing an XRF system to sort between various cast aluminum alloys.

With reference now to FIG. **14**, a block diagram illustrating a data processing ("computer") system **3400** is depicted in which aspects of embodiments of the disclosure may be implemented. (The terms "computer," "system," "computer system," and "data processing system" may be used interchangeably herein.) The computer system **107**, the automation control system **108**, aspects of the sensor system(s) **120**, and/or the vision system **110** may be configured similarly as the computer system **3400**. The computer system **3400** may employ a local bus **3405** (e.g., a peripheral component interconnect ("PCI") local bus architecture). Any suitable bus architecture may be utilized such as Accelerated Graphics Port ("AGP") and Industry Standard Architecture ("ISA"), among others. One or more processors **3415**, volatile memory **3420**, and non-volatile memory **3435** may be connected to the local bus **3405** (e.g., through a PCI Bridge (not shown)). An integrated memory controller and cache memory may be coupled to the one or more processors **3415**. The one or more processors **3415** may include one or more central processor units and/or one or more graphics processor units and/or one or more tensor processing units. Additional connections to the local bus **3405** may be made through direct component interconnection or through add-in boards. In the depicted example, a communication (e.g., network (LAN)) adapter **3425**, an I/O (e.g., small computer system interface ("SCSI") host bus) adapter **3430**, and expansion bus interface (not shown) may be connected to the local bus **3405** by direct component connection. An audio adapter (not shown), a graphics adapter (not shown), and display adapter **3416** (coupled to a display **3440**) may be connected to the local bus **3405** (e.g., by add-in boards inserted into expansion slots).

The user interface adapter **3412** may provide a connection for a keyboard **3413** and a mouse **3414**, modem (not shown), and additional memory (not shown). The I/O adapter **3430** may provide a connection for a hard disk drive **3431**, a tape drive **3432**, and a CD-ROM drive (not shown).

An operating system may be run on the one or more processors **3415** and used to coordinate and provide control of various components within the computer system **3400**. In FIG. **14**, the operating system may be a commercially available operating system. An object-oriented programming system (e.g., Java, Python, etc.) may run in conjunction with the operating system and provide calls to the operating system from programs or programs (e.g., Java, Python, etc.) executing on the system **3400**. Instructions for the operating system, the object-oriented operating system, and programs may be located on non-volatile memory **3435** storage devices, such as a hard disk drive **3431**, and may be loaded into volatile memory **3420** for execution by the processor **3415**.

Those of ordinary skill in the art will appreciate that the hardware in FIG. **14** may vary depending on the implementation. Other internal hardware or peripheral devices, such as flash ROM (or equivalent nonvolatile memory) or optical disk drives and the like, may be used in addition to or in place of the hardware depicted in FIG. **14**. Also, any of the processes of the present disclosure may be applied to a multiprocessor computer system, or performed by a plurality of such systems **3400**. For example, training of the vision system **110** may be performed by a first computer system **3400**, while operation of the vision system **110** for sorting may be performed by a second computer system **3400**.

As another example, the computer system **3400** may be a stand-alone system configured to be bootable without relying on some type of network communication interface, whether or not the computer system **3400** includes some type of network communication interface. As a further example, the computer system **3400** may be an embedded controller, which is configured with ROM and/or flash ROM providing non-volatile memory storing operating system files or user-generated data.

The depicted example in FIG. **14** and above-described examples are not meant to imply architectural limitations. Further, a computer program form of aspects of the present disclosure may reside on any computer readable storage medium (i.e., floppy disk, compact disk, hard disk, tape, ROM, RAM, etc.) used by a computer system.

As has been described herein, embodiments of the present disclosure may be implemented to perform the various functions described for identifying, tracking, classifying, and/or sorting material pieces. Such functionalities may be implemented within hardware and/or software, such as within one or more data processing systems (e.g., the data processing system **3400** of FIG. **14**), such as the previously noted computer system **107**, the vision system **110**, aspects of the sensor system(s) **120**, and/or the automation control system **108**. Nevertheless, the functionalities described herein are not to be limited for implementation into any particular hardware/software platform.

As will be appreciated by one skilled in the art, aspects of the present disclosure may be embodied as a system, process, method, and/or program product. Accordingly, various aspects of the present disclosure may take the form of an entirely hardware embodiment, an entirely software embodiment (including firmware, resident software, micro-code, etc.), or embodiments combining software and hardware aspects, which may generally be referred to herein as a "circuit," "circuitry," "module," or "system." Furthermore, aspects of the present disclosure may take the form of a program product embodied in one or more computer readable storage medium(s) having computer readable program code embodied thereon. (However, any combination of one or more computer readable medium(s) may be utilized. The computer readable medium may be a computer readable signal medium or a computer readable storage medium.)

A computer readable storage medium may be, for example, but not limited to, an electronic, magnetic, optical, electromagnetic, infrared, biologic, atomic, or semiconductor system, apparatus, controller, or device, or any suitable combination of the foregoing, wherein the computer readable storage medium is not a transitory signal per se. More specific examples (a non-exhaustive list) of the computer readable storage medium may include the following: an electrical connection having one or more wires, a portable computer diskette, a hard disk, a random access memory ("RAM") (e.g., RAM **3420** of FIG. **14**), a read-only memory ("ROM") (e.g., ROM **3435** of FIG. **14**), an erasable programmable read-only memory ("EPROM" or flash memory), an optical fiber, a portable compact disc read-only memory ("CD-ROM"), an optical storage device, a magnetic storage device (e.g., hard drive **3431** of FIG. **14**), or any suitable combination of the foregoing. In the context of this document, a computer readable storage medium may be any tangible medium that can contain or store a program for use by or in connection with an instruction execution system, apparatus, controller, or device. Program code embodied on a computer readable signal medium may be transmitted using any appropriate medium, including but not limited to wireless, wire line, optical fiber cable, RF, etc., or any suitable combination of the foregoing.

A computer readable signal medium may include a propagated data signal with computer readable program code embodied therein, for example, in baseband or as part of a carrier wave. Such a propagated signal may take any of a variety of forms, including, but not limited to, electromagnetic, optical, or any suitable combination thereof. A computer readable signal medium may be any computer readable medium that is not a computer readable storage medium and that can communicate, propagate, or transport a program for use by or in connection with an instruction execution system, apparatus, controller, or device.

The flowchart and block diagrams in the figures illustrate architecture, functionality, and operation of possible implementations of systems, methods, processes, and program products according to various embodiments of the present disclosure. In this regard, each block in the flowcharts or block diagrams may represent a module, segment, or portion of code, which includes one or more executable program instructions for implementing the specified logical function(s). It should also be noted that, in some implementations, the functions noted in the blocks may occur out of the order noted in the figures. For example, two blocks shown in succession may, in fact, be executed substantially concurrently, or the blocks may sometimes be executed in the reverse order, depending upon the functionality involved.

Modules implemented in software for execution by various types of processors (e.g., GPU 3401, CPU 3415) may, for instance, include one or more physical or logical blocks of computer instructions, which may, for instance, be organized as an object, procedure, or function. Nevertheless, the executables of an identified module need not be physically located together, but may include disparate instructions stored in different locations which, when joined logically together, include the module and achieve the stated purpose for the module. Indeed, a module of executable code may be a single instruction, or many instructions, and may even be distributed over several different code segments, among different programs, and across several memory devices. Similarly, operational data (e.g., material classification libraries described herein) may be identified and illustrated herein within modules, and may be embodied in any suitable form and organized within any suitable type of data structure. The operational data may be collected as a single data set, or may be distributed over different locations including over different storage devices. The data may provide electronic signals on a system or network.

These program instructions may be provided to one or more processors and/or controller(s) of a general purpose computer, special purpose computer, or other programmable data processing apparatus (e.g., controller) to produce a machine, such that the instructions, which execute via the processor(s) (e.g., GPU 3401, CPU 3415) of the computer or other programmable data processing apparatus, create circuitry or means for implementing the functions/acts specified in the flowchart and/or block diagram block or blocks.

It will also be noted that each block of the block diagrams and/or flowchart illustrations, and combinations of blocks in the block diagrams and/or flowchart illustrations, can be implemented by special purpose hardware-based systems (e.g., which may include one or more graphics processing units (e.g., GPU 3401)) that perform the specified functions or acts, or combinations of special purpose hardware and computer instructions. For example, a module may be implemented as a hardware circuit including custom VLSI circuits or gate arrays, off-the-shelf semiconductors such as logic chips, transistors, controllers, or other discrete components. A module may also be implemented in programmable hardware devices such as field programmable gate arrays, programmable array logic, programmable logic devices, or the like.

Computer program code, i.e., instructions, for carrying out operations for aspects of the present disclosure may be written in any combination of one or more programming languages, including an object oriented programming language such as Java, Smalltalk, Python, C++, or the like, conventional procedural programming languages, such as the "C" programming language or similar programming languages, programming languages such as MATLAB or LabVIEW, or any of the machine learning software disclosed herein. The program code may execute entirely on the user's computer system, partly on the user's computer system, as a stand-alone software package, partly on the user's computer system (e.g., the computer system utilized for sorting) and partly on a remote computer system (e.g., the computer system utilized to train the machine learning system), or entirely on the remote computer system or server. In the latter scenario, the remote computer system may be connected to the user's computer system through any type of network, including a local area network ("LAN") or a wide area network ("WAN"), or the connection may be made to an external computer system (for example, through the Internet using an Internet Service Provider). As an example of the foregoing, various aspects of the present disclosure may be configured to execute on one or more of the computer system **107**, automation control system **108**, the vision system **110**, and aspects of the sensor system(s) **120**.

These program instructions may also be stored in a computer readable storage medium that can direct a computer system, other programmable data processing apparatus, controller, or other devices to function in a particular manner, such that the instructions stored in the computer readable medium produce an article of manufacture including instructions which implement the function/act specified in the flowchart and/or block diagram block or blocks.

The program instructions may also be loaded onto a computer, other programmable data processing apparatus, controller, or other devices to cause a series of operational steps to be performed on the computer, other programmable apparatus or other devices to produce a computer implemented process such that the instructions which execute on the computer or other programmable apparatus provide processes for implementing the functions/acts specified in the flowchart and/or block diagram block or blocks.

One or more databases may be included in a host for storing and providing access to data for the various implementations. One skilled in the art will also appreciate that, for security reasons, any databases, systems, or components of the present disclosure may include any combination of databases or components at a single location or at multiple locations, wherein each database or system may include any of various suitable security features, such as firewalls, access codes, encryption, de-encryption and the like. The database may be any type of database, such as relational, hierarchical, object-oriented, and/or the like. Common database products that may be used to implement the databases include DB2 by IBM, any of the database products available from Oracle Corporation, Microsoft Access by Microsoft Corporation, or any other database product. The database may be organized in any suitable manner, including as data tables or lookup tables.

Association of certain data (e.g., for each of the scrap pieces processed by a sorting system described herein) may be accomplished through any data association technique known and practiced in the art. For example, the association may be accomplished either manually or automatically. Automatic association techniques may include, for example, a database search, a database merge, GREP, AGREP, SQL, and/or the like. The association step may be accomplished by a database merge function, for example, using a key field in each of the manufacturer and retailer data tables. A key field partitions the database according to the high-level class of objects defined by the key field. For example, a certain class may be designated as a key field in both the first data table and the second data table, and the two data tables may then be merged on the basis of the class data in the key field. In these embodiments, the data corresponding to the key field in each of the merged data tables is preferably the same. However, data tables having similar, though not identical, data in the key fields may also be merged by using AGREP, for example.

Reference is made herein to "configuring" a device or a device "configured to" perform some function. It should be understood that this may include selecting predefined logic blocks and logically associating them, such that they provide particular logic functions, which includes monitoring or control functions. It may also include programming computer software-based logic of a retrofit control device, wiring discrete hardware components, or a combination of any or all of the foregoing. Such configured devises are physically designed to perform the specified function or functions.

In the descriptions herein, numerous specific details are provided, such as examples of programming, software modules, user selections, network transactions, database queries, database structures, hardware modules, hardware circuits, hardware chips, controllers, etc., to provide a thorough understanding of embodiments of the disclosure. One skilled in the relevant art will recognize, however, that the disclosure may be practiced without one or more of the specific details, or with other methods, components, materials, and so forth. In other instances, well-known structures, materials, or operations may be not shown or described in detail to avoid obscuring aspects of the disclosure.

Reference throughout this specification to "an embodiment," "embodiments," or similar language means that a particular feature, structure, or characteristic described in connection with the embodiments is included in at least one embodiment of the present disclosure. Thus, appearances of the phrases "in one embodiment," "in an embodiment," "embodiments," "certain embodiments," "various embodiments," and similar language throughout this specification may, but do not necessarily, all refer to the same embodiment. Furthermore, the described features, structures, aspects, and/or characteristics of the disclosure may be combined in any suitable manner in one or more embodiments. Correspondingly, even if features may be initially claimed as acting in certain combinations, one or more features from a claimed combination can in some cases be excised from the combination, and the claimed combination can be directed to a sub-combination or variation of a sub-combination.

Benefits, advantages, and solutions to problems have been described above with regard to specific embodiments. However, the benefits, advantages, solutions to problems, and any element(s) that may cause any benefit, advantage, or solution to occur or become more pronounced may be not to be construed as critical, required, or essential features or elements of any or all the claims. Further, no component described herein is required for the practice of the disclosure unless expressly described as essential or critical.

Those skilled in the art having read this disclosure will recognize that changes and modifications may be made to the embodiments without departing from the scope of the present disclosure. It should be appreciated that the particular implementations shown and described herein may be illustrative of the disclosure and its best mode and may be not intended to otherwise limit the scope of the present disclosure in any way. Other variations may be within the scope of the following claims.

While this specification contains many specifics, these should not be construed as limitations on the scope of the disclosure or of what can be claimed, but rather as descriptions of features specific to particular implementations of the disclosure. Headings herein may be not intended to limit the disclosure, embodiments of the disclosure or other matter disclosed under the headings.

Herein, the term "or" may be intended to be inclusive, wherein "A or B" includes A or B and also includes both A and B. As used herein, the term "and/or" when used in the context of a listing of entities, refers to the entities being present singly or in combination. Thus, for example, the phrase "A, B, C, and/or D" includes A, B, C, and D individually, but also includes any and all combinations and subcombinations of A, B, C, and D.

The terminology used herein is for the purpose of describing particular embodiments only and is not intended to be limiting of the disclosure. As used herein, the singular forms "a," "an," and "the" may be intended to include the plural forms as well, unless the context clearly indicates otherwise.

The corresponding structures, materials, acts, and equivalents of all means or step plus function elements in the claims below may be intended to include any structure, material, or act for performing the function in combination with other claimed elements as specifically claimed.

As used herein with respect to an identified property or circumstance, "substantially" refers to a degree of deviation that is sufficiently small so as to not measurably detract from the identified property or circumstance. The exact degree of deviation allowable may in some cases depend on the specific context.

As used herein, a plurality of items, structural elements, compositional elements, and/or materials may be presented in a common list for convenience. However, these lists should be construed as though each member of the list is individually identified as a separate and unique member. Thus, no individual member of such list should be construed as a defacto equivalent of any other member of the same list solely based on their presentation in a common group without indications to the contrary.

Unless defined otherwise, all technical and scientific terms (such as acronyms used for chemical elements within the periodic table) used herein have the same meaning as commonly understood to one of ordinary skill in the art to which the presently disclosed subject matter belongs. Although any methods, devices, and materials similar or equivalent to those described herein can be used in the practice or testing of the presently disclosed subject matter, representative methods, devices, and materials are now described.

Unless otherwise indicated, all numbers expressing quantities of ingredients, reaction conditions, and so forth used in the specification and claims are to be understood as being modified in all instances by the term "about." Accordingly, unless indicated to the contrary, the numerical parameters set forth in this specification and attached claims are approximations that can vary depending upon the desired properties sought to be obtained by the presently disclosed subject matter. As used herein, the term "about," when referring to a value or to an amount of mass, weight, time, volume, concentration or percentage is meant to encompass variations of in some embodiments ±20%, in some embodiments ±10%, in some embodiments ±5%, in some embodiments ±1%, in some embodiments ±0.5%, and in some embodiments ±0.1% from the specified amount, as such variations are appropriate to perform the disclosed method.

What is claimed is:

1. A method for sorting a plurality of metal alloy pieces into a first collection of metal alloy pieces having a first metal alloy composition and a second collection of metal alloy pieces having one or more second metal alloy compositions different from the first metal alloy composition, the method comprising:

conveying the plurality of metal alloy pieces by a conveyor system at a predetermined speed;

determining an approximate length of each of the plurality of metal scrap pieces along a line parallel to a direction of travel of the plurality of metal alloy pieces by the conveyor system, wherein the determining the approximate length of each of the plurality of metal alloy pieces comprises measuring the approximate length of each of the plurality of metal alloys scrap pieces as they travel at the predetermined speed past a distance measuring device;

exposing the plurality of metal scrap pieces to x-rays emitted by an x-ray source of an x-ray fluorescence ("XRF") system, and detecting, by the XRF system, x-ray fluorescence signals emitted by the plurality of metal scrap pieces in response to the x-rays emitted by the x-ray source;

wherein the XRF system is configured to measure an XRF spectrum emitted from a particular one of each of the plurality of metal alloy pieces only for a time period determined as a function of the measured approximate length for the particular one of each of the plurality of metal alloy pieces, wherein the time period is determined as a function of the measured approximate length of the particular one of each of the plurality of metal alloy pieces and the predetermined speed so that only the XRF spectrum emitted from the particular one of each of the plurality of metal alloy pieces is measured and not from an environment surrounding the particular one of each of the plurality of metal alloy pieces;

classifying a first one of the plurality of metal alloy pieces as having the first metal alloy composition as a result of acquired x-ray fluorescence detected from the first one of the plurality of metal alloy pieces using the XRF system; and

sorting the first one of the plurality of metal alloy pieces from the plurality of metal alloy pieces in response to classifying the first one of the plurality of metal alloy pieces as having the first metal alloy composition.

2. The method as recited in claim **1**, further comprising:

classifying a second one of the plurality of metal alloy pieces as having the second metal alloy composition as a result of acquired x-ray fluorescence detected from the second one of the plurality of metal alloy pieces using the XRF system; and

sorting the second one of the plurality of metal alloy pieces from the plurality of metal alloy pieces in response to classifying the second one of the plurality of metal alloy pieces as having the second metal alloy composition.

3. The method as recited in claim **2**, wherein the plurality of metal alloy pieces are aluminum alloy scrap pieces.

4. The method as recited in claim **3**, wherein the aluminum alloy scrap pieces comprise at least two different cast aluminum alloys.

5. The method as recited in claim **4**, wherein the at least two different cast aluminum alloys are selected from a group consisting of cast aluminum alloy 319, cast aluminum alloy 356, cast aluminum alloy 384, cast aluminum alloy 360, and cast aluminum alloy 380.

6. The method as recited in claim **4**, wherein the first one of the plurality of metal alloy pieces is classified as having a first cast aluminum alloy, and wherein the second one of the plurality of metal alloy pieces is classified as having a second cast aluminum alloy different from the first cast aluminum alloy.

7. The method as recited in claim **1**, wherein the plurality of metal alloy pieces comprise scrap pieces composed of a wrought aluminum alloy, scrap pieces composed of a first cast aluminum alloy, and scrap pieces composed of a second cast aluminum alloy different from the first cast aluminum alloy, the method further comprising sorting out scrap pieces that have been classified as composed of a wrought aluminum alloy before exposing a remainder of the plurality of metal scrap pieces to the x-rays emitted by the x-ray source of the XRF system in order to classify and sort the scrap pieces composed of the first cast aluminum alloy from the scrap pieces composed of the second cast aluminum alloy.

8. The method as recited in claim **7**, wherein the scrap pieces that have been classified as composed of the wrought aluminum alloy were classified using an artificial intelligence system as a function of a knowledge base containing a previously generated library of observed characteristics associated with wrought aluminum scrap pieces.

9. The method as recited in claim **7**, further comprising classifying and sorting between the scrap pieces composed of different wrought aluminum alloys.

10. The method as recited in claim **1**, wherein one or more x-ray detectors of the XRF system acquire the XRF spectrum comprising energy counts for a plurality of channels of x-rays fluoresced by each of the plurality of metal alloy pieces as they travel within a proximity of the x-ray beam emitted from the XRF system, wherein each of the plurality of channels represents a different element within each of the plurality of metal alloy pieces, wherein the energy counts for each of the plurality of channels are accumulated as running total energy counts for the plurality of metal alloy pieces, wherein the energy counts for each of the plurality of channels for the particular one of each of the plurality of metal alloy pieces is determined by subtracting the accumulated running total energy counts received by the x-ray detector for previously scanned metal alloy pieces from the accumulated running total energy counts received by the x-ray detector for the particular one of the plurality of metal alloy pieces on a per channel basis.

11. The method as recited in claim **10**, further comprising:

normalizing a net peak area of each of the energy counts for each of the plurality of channels to generate an elemental composition signature for the first one of the plurality of metal alloy pieces; and

comparing the elemental composition signature for the first one of the plurality of metal alloy pieces on an element-by-element basis to one or more known elemental composition signatures, wherein the one or more known elemental composition signatures each correspond to a different aluminum alloy composition, wherein the first one of the plurality of metal alloy pieces is classified as having the first metal alloy composition when the elemental composition signature for the first one of the plurality of metal alloy pieces matches with the known elemental composition signature corresponding to the first metal alloy composition.

12. A system for sorting metal alloys comprising:

a conveyor system configured to convey a plurality of received metal alloy pieces at a predetermined speed;

a distance measuring device configured to determine an approximate length for each of the plurality of metal alloy pieces along a line parallel to a direction of travel of the plurality of metal alloy pieces;

an XRF system configured to emit x-rays from an x-ray source towards each of the plurality of metal alloy pieces and to detect x-ray fluorescence signals emitted by the plurality of metal alloy pieces in response to the x-rays emitted by the x-ray source;

the XRF system configured to determine separate XRF spectra for each of the plurality of metal alloy pieces only during a time period determined as a function of the approximate length and the predetermined speed so that only the XRF spectrum emitted from a respective metal alloy piece is measured and not from an environment surrounding the respective metal alloy piece;

circuitry configured to classify a first one of the plurality of metal alloy pieces as having the first metal alloy composition and classify a second one of the plurality of metal alloy pieces as having the second metal alloy composition, wherein metal alloy compositions of the plurality of metal alloy pieces are classified as a result of acquired x-ray fluorescence detected from each of the plurality of metal alloy pieces using the XRF system; and

a sorting device configured to sort the first one of the plurality of metal alloy pieces from the second one of the metal alloy pieces in response to (1) classifying the first one of the plurality of metal alloy pieces as having the first metal alloy composition, and (2) classifying the second one of the plurality of metal alloy pieces as having the second metal alloy composition.

13. The system as recited in claim **12**, wherein the distance measuring device further comprises a light source to determine the approximate length of each of the plurality of metal alloy pieces.

14. The system as recited in claim **12**, wherein first and second ones of the plurality of metal alloy pieces contain different aluminum alloys.

15. The system as recited in claim **14**, wherein the aluminum alloy scrap pieces comprise at least two different cast aluminum alloys.

16. The system as recited in claim **15**, wherein the at least two different cast aluminum alloys are selected from a group consisting of cast aluminum alloy 319, cast aluminum alloy 356, cast aluminum alloy 384, cast aluminum alloy 360, and cast aluminum alloy 380, wherein the first one of the plurality of metal alloy pieces is classified as having a first cast aluminum alloy, and wherein the second one of the plurality of metal alloy pieces is classified as having a second cast aluminum alloy different from the first cast aluminum alloy.

17. The system as recited in claim **12**, wherein the plurality of metal alloy pieces comprise scrap pieces composed of a wrought aluminum alloy, scrap pieces composed of a first cast aluminum alloy, and scrap pieces composed of a second cast aluminum alloy different from the first cast aluminum alloy, the system further comprising another sorting device configured to sort out scrap pieces that have been classified as composed of a wrought aluminum alloy before exposing a remainder of the plurality of metal scrap pieces to the x-rays emitted by the x-ray source of the XRF system in order to classify and sort the scrap pieces composed of the first cast aluminum alloy from the scrap pieces composed of the second cast aluminum alloy.

18. The system as recited in claim **17**, wherein the scrap pieces that have been classified as composed of the wrought aluminum alloy were classified using a neural network as a function of a knowledge base containing a previously generated library of observed characteristics associated with wrought aluminum scrap pieces.

19. The system as recited in claim **17**, further comprising classifying and sorting between the scrap pieces composed of different wrought aluminum alloys.

20. The system as recited in claim **12**, wherein one or more x-ray detectors of the XRF system acquire the XRF spectrum comprising energy counts for a plurality of channels of x-rays fluoresced by each of the plurality of metal alloy pieces as they travel within a proximity of the x-ray beam emitted from the XRF system, wherein each of the plurality of channels represents a different element within each of the plurality of metal alloy pieces, wherein the energy counts for each of the plurality of channels are accumulated as running total energy counts for the plurality of metal alloy pieces, wherein the energy counts for each of the plurality of channels for the particular one of each of the plurality of metal alloy pieces is determined by subtracting the accumulated running total energy counts received by the x-ray detector for previously scanned metal alloy pieces from the accumulated running total energy counts received by the x-ray detector for the particular one of the plurality of metal alloy pieces on a per channel basis.

21. The system as recited in claim **12**, wherein the first and second metal alloy compositions fall within a same aluminum alloy series.

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