



(12) **DEMANDE DE BREVET CANADIEN
CANADIAN PATENT APPLICATION**

(13) **A1**

(86) Date de dépôt PCT/PCT Filing Date: 2017/10/18
(87) Date publication PCT/PCT Publication Date: 2018/04/26
(85) Entrée phase nationale/National Entry: 2019/04/11
(86) N° demande PCT/PCT Application No.: US 2017/057243
(87) N° publication PCT/PCT Publication No.: 2018/075674
(30) Priorité/Priority: 2016/10/22 (US15/331,841)

(51) Cl.Int./Int.Cl. *G06N 3/04* (2006.01),
A01G 3/00 (2006.01), *A01G 3/08* (2006.01),
G06K 9/00 (2006.01), *G06T 1/40* (2006.01),
G06T 7/10 (2017.01)
(71) Demandeur/Applicant:
BURDEN, KEITH CHARLES, US
(72) Inventeur/Inventor:
BURDEN, KEITH CHARLES, US
(74) Agent: BENOIT & COTE INC.

(54) Titre : **SYSTEME D'ELAGAGE OU DE RECOLTE AUTOMATISE POUR FEUILLAGE A MORPHOLOGIE COMPLEXE**

(54) Title: **AUTOMATED PRUNING OR HARVESTING SYSTEM FOR COMPLEX MORPHOLOGY FOLIAGE**

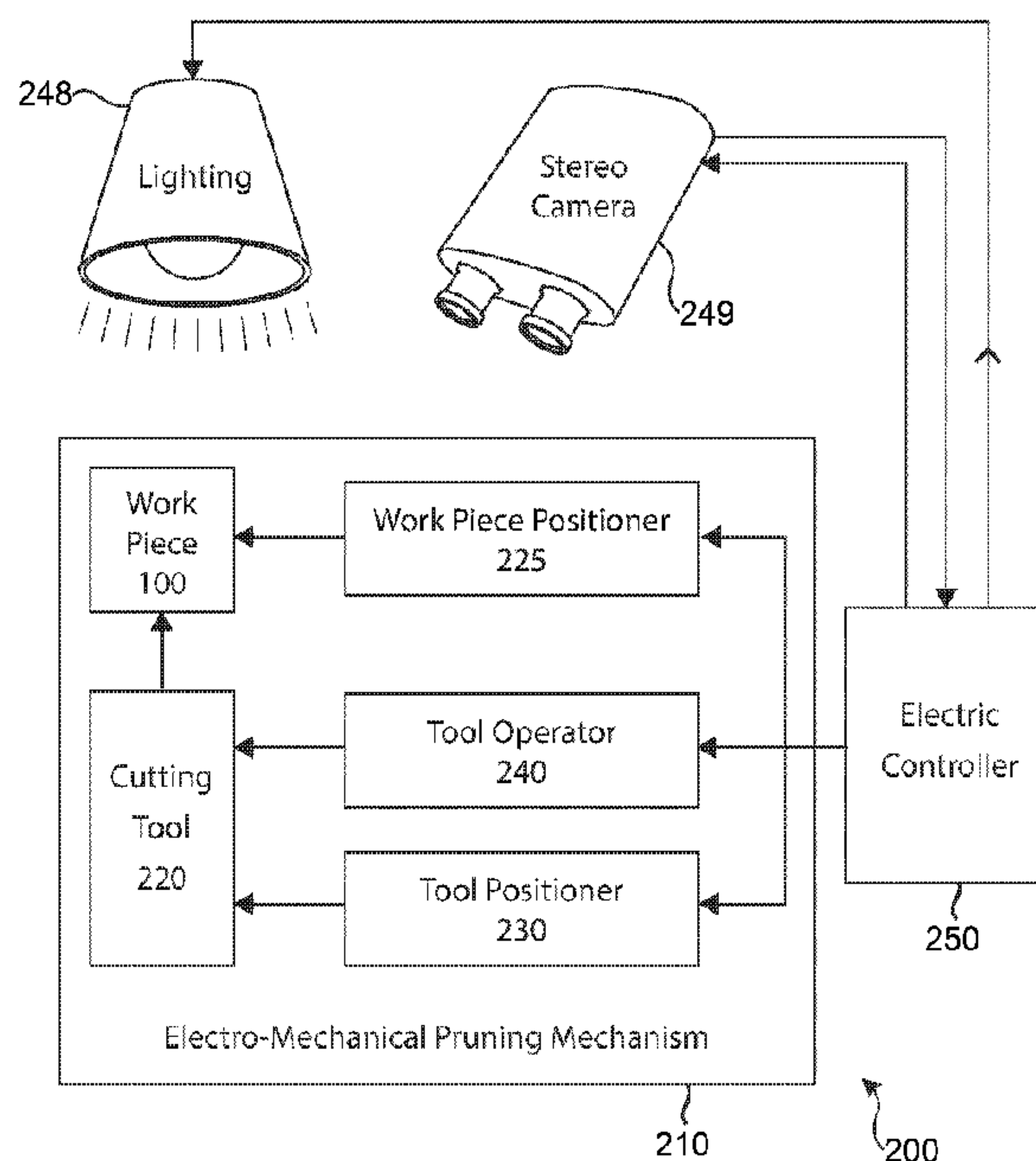


FIG. 1

(57) **Abrégé/Abstract:**

Method and apparatus for automated operations, such as pruning, harvesting, spraying and/or maintenance, on plants, and particularly plants with foliage having features on many length scales or a wide spectrum of length scales, such as female flower buds of the marijuana plant. The invention utilizes a convolutional neural network for image segmentation classification and/or the determination of features. The foliage is imaged stereoscopically to produce a three-dimensional surface image, a first neural network determines regions to be operated on, and a second neural network determines how an operation tool operates on the foliage. For pruning of resinous foliage the cutting tool is heated or cooled to avoid having the resins make the cutting tool inoperable.

(12) INTERNATIONAL APPLICATION PUBLISHED UNDER THE PATENT COOPERATION TREATY (PCT)

(19) World Intellectual Property
Organization
International Bureau

(43) International Publication Date
26 April 2018 (26.04.2018)



(10) International Publication Number
WO 2018/075674 A1

(51) International Patent Classification:

G06F 15/18 (2006.01) *G06N 3/08* (2006.01)
G06K 9/00 (2006.01) *A01G 3/00* (2006.01)
G06T 7/00 (2017.01) *B23Q 17/00* (2006.01)

(21) International Application Number:

PCT/US2017/057243

(22) International Filing Date:

18 October 2017 (18.10.2017)

(25) Filing Language:

English

(26) Publication Language:

English

(30) Priority Data:

15/331,841 22 October 2016 (22.10.2016) US

(72) Inventor; and

(71) Applicant: **BURDEN, Keith Charles** [US/US]; 1035 22nd Avenue, Unit 15, Oakland, California 94606 (US).

(74) Agent: **SHAW, Laurence, Jay et al.**; 3627 Sacramento Street, San Francisco, CA 94118 (US).

(81) Designated States (*unless otherwise indicated, for every kind of national protection available*): AE, AG, AL, AM, AO, AT, AU, AZ, BA, BB, BG, BH, BN, BR, BW, BY, BZ, CA, CH, CL, CN, CO, CR, CU, CZ, DE, DJ, DK, DM, DO, DZ, EC, EE, EG, ES, FI, GB, GD, GE, GH, GM, GT, HN, HR, HU, ID, IL, IN, IR, IS, JO, JP, KE, KG, KH, KN, KP,

KR, KW, KZ, LA, LC, LK, LR, LS, LU, LY, MA, MD, ME, MG, MK, MN, MW, MX, MY, MZ, NA, NG, NI, NO, NZ, OM, PA, PE, PG, PH, PL, PT, QA, RO, RS, RU, RW, SA, SC, SD, SE, SG, SK, SL, SM, ST, SV, SY, TH, TJ, TM, TN, TR, TT, TZ, UA, UG, US, UZ, VC, VN, ZA, ZM, ZW.

(84) Designated States (*unless otherwise indicated, for every kind of regional protection available*): ARIPO (BW, GH, GM, KE, LR, LS, MW, MZ, NA, RW, SD, SL, ST, SZ, TZ, UG, ZM, ZW), Eurasian (AM, AZ, BY, KG, KZ, RU, TJ, TM), European (AL, AT, BE, BG, CH, CY, CZ, DE, DK, EE, ES, FI, FR, GB, GR, HR, HU, IE, IS, IT, LT, LU, LV, MC, MK, MT, NL, NO, PL, PT, RO, RS, SE, SI, SK, SM, TR), OAPI (BF, BJ, CF, CG, CI, CM, GA, GN, GQ, GW, KM, ML, MR, NE, SN, TD, TG).

Published:

- with international search report (Art. 21(3))
- before the expiration of the time limit for amending the claims and to be republished in the event of receipt of amendments (Rule 48.2(h))

(54) Title: AUTOMATED PRUNING OR HARVESTING SYSTEM FOR COMPLEX MORPHOLOGY FOLIAGE

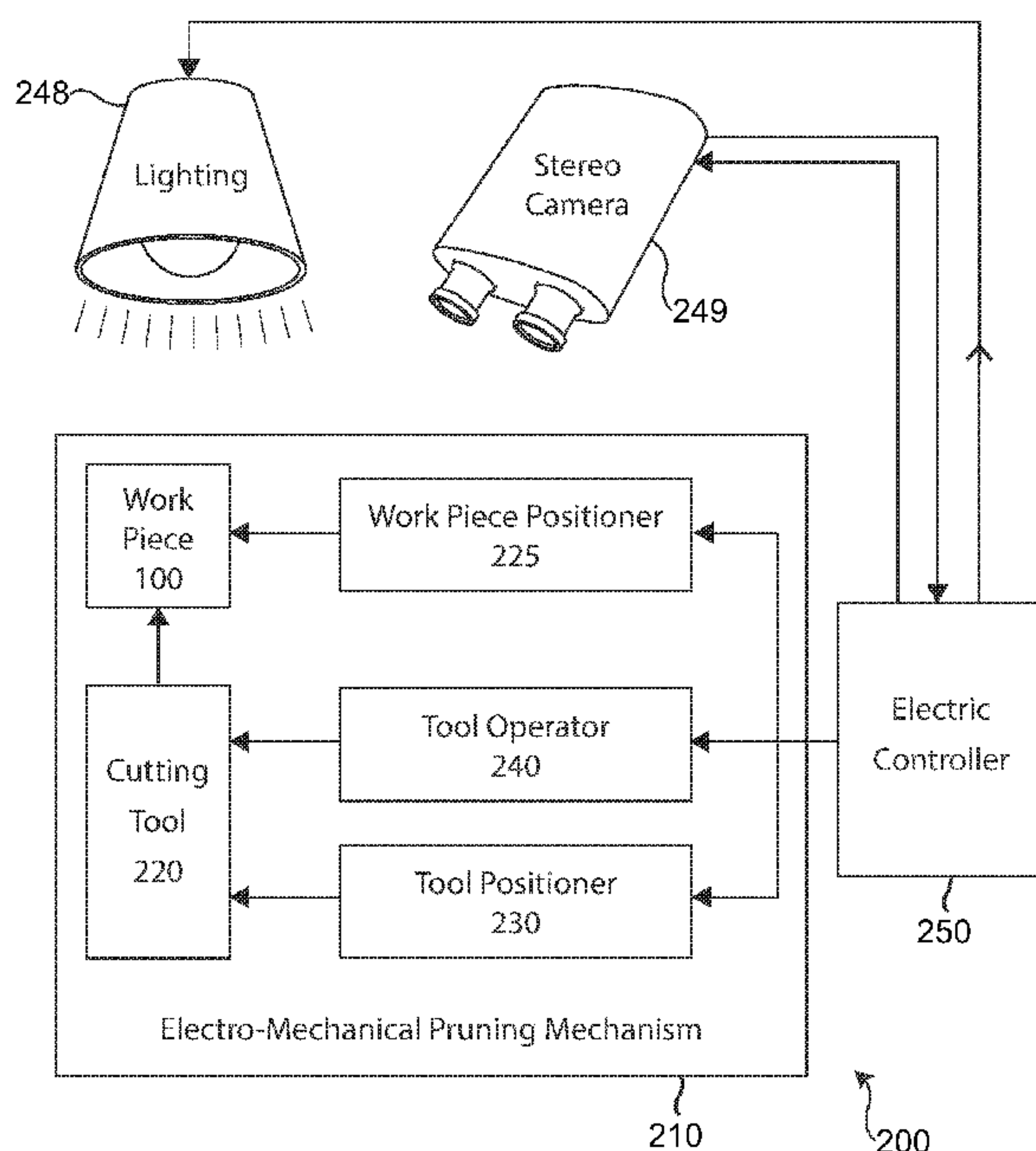


FIG. 1

(57) Abstract: Method and apparatus for automated operations, such as pruning, harvesting, spraying and/or maintenance, on plants, and particularly plants with foliage having features on many length scales or a wide spectrum of length scales, such as female flower buds of the marijuana plant. The invention utilizes a convolutional neural network for image segmentation classification and/or the determination of features. The foliage is imaged stereoscopically to produce a three-dimensional surface image, a first neural network determines regions to be operated on, and a second neural network determines how an operation tool operates on the foliage. For pruning of resinous foliage the cutting tool is heated or cooled to avoid having the resins make the cutting tool inoperable.

5 **AUTOMATED PRUNING OR HARVESTING SYSTEM FOR COMPLEX**
 MORPHOLOGY FOLIAGE

Related Applications

 This application claims the benefit of U.S. Patent Application No. 15/331,841
10 filed October 22, 2016, which is incorporated herein by reference in its entirety for all
 purposes.

Field of the Invention

 The present invention relates to apparatus and method for the automation of
15 agricultural processes, and more particularly to apparatus and method for robotics for
 automated pruning, harvesting, spraying and/or maintenance of agricultural crops.

 The present invention also relates to apparatus and method for differentiation of
 variations in foliage, including subtle variations such as the detection of variations in the
 health of foliage, maturity of foliage, chemical content of foliage, ripeness of fruit,
20 locations of insects or insect infestations, etc.

 The present invention also relates to object recognition, particularly object
 recognition utilizing multiple types of image information, such multiple types of image
 information for instance including texture and/or shape and/or color.

 The present invention also relates to the training and use of neural networks, and
25 particularly the training and use of neural networks for image segmentation classification
 and/or the extraction of features in objects having features on many length scales or a
 wide spectrum of length scales.

Background of the Invention

30 In the present specification, “foliage” is meant to be a general term for plant
 matter which includes leaves, stems, branches, flowers, fruit, berries, roots, etc. In the

present specification, “harvest fruit” is meant to include any plant matter, whether fruit, vegetable, leaf, berry, legume, melon, stalk, stem, branch, root, etc., which is to be harvested. In the present specification, “pruning target” is meant to include any plant matter, whether fruit, vegetable, leaf, berry, legume, melon, stalk, stem, branch, root, etc., which is retained or pruned to be discarded. In the present specification, “color” is meant to include any information obtained by analysis of the reflection of electromagnetic radiation from a target. In the present specification, a “feature characteristic” of a workpiece or a “workpiece feature” is meant to include any type of element or component such as leaves, stems, branches, flowers, fruit, berries, roots, etc., or any “color” characteristic such as color or texture. In the present specification, a "neural network" may be any type of deep learning computational system.

Marijuana is a genus of flowering plants that includes three different species: *Cannabis sativa*, *Cannabis indica* and *Cannabis ruderalis*. Marijuana plants produce a unique family of terpeno-phenolic compounds called cannabinoids. Over 85 types of cannabinoids from marijuana have been identified, including tetrahydrocannabinol (THC) and cannabidiol (CBD). Strains of marijuana for recreational use have been bred to produce high levels of THC, the major psychoactive cannabinoid in marijuana, and strains of marijuana for medical use have been bred to produce high levels of THC and/or CBD, which is considerably less psychoactive than THC and has been shown to have a wide range of medical applications. Cannabinoids are known to be effective as analgesic and antiemetic agents, and have shown promise or usefulness in treating diabetes, glaucoma, certain types of cancer and epilepsy, Dravet Syndrome, Alzheimer's disease, Parkinson's disease, schizophrenia, Crohn's, and brain damage from strokes, concussions and other trauma. Another useful and valuable chemical produced by marijuana plants, and particularly the flowers, is terpenes. Terpenes, like cannabinoids, can bind to receptors in the brain and, although subtler in their effects than THC, are also psychoactive. Some terpenes are aromatic and are commonly used for aromatherapy. However, chemical synthesis of terpenes is challenging because of their complex structure, so the application of the present invention to marijuana plants is valuable since it produces an increased efficiency in the harvesting of terpenes and cannabinoids. Billions of dollars has been spent in the research, development and

patenting of cannabis for medical use. Twenty of the fifty U.S. states and the District of Columbia have recognized the medical benefits of cannabis and have decriminalized its medical use. Recently, U.S. Attorney General Eric Holder announced that the federal government would allow states to create a regime that would regulate and implement the legalization of cannabis, including loosening banking restrictions for cannabis dispensaries and growers.

Marijuana plants may be male, female, or hermaphrodite (*i.e.*, of both sexes). The flowers of the female marijuana plant have the highest concentration of cannabinoids and terpenes. In the current specification, the term “bud” refers to a structure comprised of a volume of individual marijuana flowers that have become aggregated through means of intertwined foliage and/or adhesion of their surfaces. As exemplified by an exemplary female bud (100) shown in FIG. 6A, the flower buds of the female plant generally have a very complex structure. Furthermore, the flower buds of the female plant have an extremely wide spectrum of the morphologies across strains and even from plant to plant. The cannabinoids and terpenes in marijuana are predominantly located in resin droplets, which may appear white, yellow or red, at the tips of small, hair-like stalks which are typically less than 1 mm in height. These small hairs and resin droplets are known as trichomes. Stems (630), shade leaves (620) (*i.e.*, the palmate leaves which emanate from the stem (630)), and sugar leaves (610) (*i.e.*, the isolated leaves which emanate from within and are involuted with the high-resin portions of the bud (100)) generally have a low surface density of trichomes, and it is therefore preferable to trim them from the buds before consumption or processing. The shade leaves (620) and particularly the sugar leaves (610) come in a wide variety of shapes and sizes, and sprout from a variety of locations, including from crannies and crevices of the bud (100). According to conventional practice, the shade leaves (620) and sugar leaves (610) are removed by pruning them (110) from the bud (100) by hand with a scissor, before consumption or further processing. Developing a system for automated trimming of stems (630), shade leaves (620), and sugar leaves (610) involves the challenges of robust object recognition and designing robotics for the pruning of complex and/or irregular shapes. In fact, it seems typical marijuana buds (100) have a more complex spectrum of length scale features than any other type of plant or plant component in general agricultural use, and

possibly a more complex spectrum of length scale features than any other type of plant or plant component. Therefore, the challenges involved in implementing the preferred embodiment described herein is to provide a system which is adaptable to almost any agricultural crop, essentially any agricultural operation, and many types of workpieces
5 beyond agriculture.

Therefore, although a preferred embodiment of the present invention described in the present specification is an automated system for trimming stems, shade leaves, and sugar leaves from the buds of marijuana plants, it should be understood that the present invention can be broadly applied to automated pruning, harvesting, spraying, or other
10 maintenance operations for a very wide variety of agricultural crops. A large fraction of the cost of production of many agricultural crops is due to the human labor involved, and effective automation of pruning, trimming, harvesting, spraying and/or other maintenance operations for agricultural crops can reduce costs and so is of enormous economic importance.

15 It is therefore an object of the present invention to provide an apparatus and method for the automation of pruning, harvesting, spraying or other forms of maintenance of plants, particularly agricultural crops.

It is another object of the present invention to provide an apparatus and method for the automation of pruning, harvesting, spraying or other maintenance operations for
20 plants having complex morphologies or for a variety of plants of differing, and perhaps widely differing, morphologies.

It is another object of the present invention to provide an apparatus and method for automated pruning, harvesting, spraying or other maintenance operations for agricultural crops which analyzes and utilizes variations, and perhaps subtle variations, in
25 color, shape, texture, chemical composition, or location of the harvest fruit, pruning targets, or surrounding foliage.

It is another object of the present invention to provide an apparatus and method for detection of differences, and perhaps subtle differences, in the health, maturity, or types of foliage.

30 It is another object of the present invention to provide an apparatus and method for pruning of plants having complex morphologies utilizing a neural network, and more

particularly a neural network where the complex morphologies prevents unsupervised training of the network, for instance, because autocorrelations do not converge.

It is another object of the present invention to provide an apparatus and method for pruning of plants having complex morphologies using a scissor-type tool.

5 It is another object of the present invention to provide a scissor-type tool for pruning of resinous plants.

It is another object of the present invention to provide a scissor-type tool for pruning of resinous plants with a means and/or mechanism for overcoming resin build-up and/or clogging on the tool.

10 Additional objects and advantages of the invention will be set forth in the description which follows, and will be obvious from the description or may be learned by practice of the invention. The objects and advantages of the invention may be realized and obtained by means of the instrumentalities and combinations particularly pointed out in the claims.

15

Brief Description of the Drawings

Figure 1 is a schematic of the system of a preferred embodiment of the present invention.

20 Figure 2 shows an electro-mechanical apparatus according to the preferred embodiment of the present invention.

Figure 3A shows the pruning process according to the preferred embodiment of the present invention.

Figure 3B shows the training process according to the preferred embodiment of the present invention.

25 Figure 4 shows the process of analysis of a stereoscopic image of a workpiece to produce the depth, texture and color data used by the neural network according to a first preferred embodiment of the present invention.

Figure 5 shows the convolution neural network according to the preferred embodiment of the present invention for processing of the depth, texture and color data to produce information required for pruning.

30

Figure 6A shows the convex hull vertices of an exemplary cannabis bud.

Figure 6B shows the convex hull vertices without depiction of the exemplary cannabis bud from which the convex hull vertices were generated.

Figure 7A shows an exemplary workpiece with shade and sugar leaves on the lefthand side.

5 Figure 7B shows human-identified regions where shade and sugar leaves are located on the workpiece of Figure 7A.

Figure 7C shows an exemplary workpiece with many large shade and sugar leaves.

10 Figure 7D shows an exemplary workpiece with smaller shade and sugar leaves than those of the workpiece of Figure 7C.

Figure 7E shows regions on the workpiece of Figure 7C which have been identified by a convolution neural network as having a high density of trichomes as white.

15 Figure 7F shows regions on the workpiece of Figure 7D which have been identified by a convolution neural network as having a high density of trichomes as white.

Figure 7G shows regions on the workpiece of Figure 7C which have been identified by a convolution neural network as having a low density of trichomes as white.

20 Figure 7H shows regions on the workpiece of Figure 7D which have been identified by a convolution neural network as having a low density of trichomes as white.

Figure 8 shows a schematic of a convolutional neural network according to an alternative preferred embodiment for classification of low trichome density regions on a marijuana bud.

25 Figure 9A shows a top view of a heated, spring-biased scissor-type cutting tool according to the present invention.

Figure 9B shows a side view of the heated, spring-biased scissor-type cutting tool of Figure 9A.

Figure 9C shows a front view of the heated, spring-biased scissor-type cutting tool of Figure 9A.

30

Figure 10 shows a process of training of a convolution neural network according to the present invention.

Figure 11 shows the process of use of the convolution neural network of Figure 11 according to the present invention.

5 Figure 12A shows an alternate embodiment of a cutting tool positioning and workpiece positioning apparatus according to the present invention.

Figure 12B is a schematic cross-sectional view of the carriage unit for the grip mechanism.

10 Figure 13 shows a process for generating convex hulls around regions of low trichome density.

Figure 14 shows a process for calculating and executing tool positioning to cut foliage based on convex hull information.

Detailed Description of a Preferred Embodiment

15 A schematic of the system (200) of a preferred embodiment of the present invention is shown in FIG. 1. The system (200) has an electro-mechanical pruning mechanism (210), a lighting system (248), a stereoscopic camera (249), and an electric controller (250). The electric controller (250) may be implemented in software or hardware or both, and may for instance be a desktop computer, a laptop computer, a
20 dedicated microprocessor, etc. When not explicitly mentioned in the present specification, control and processing operations are performed by the electric controller (250). As discussed below, the electric controller (250) includes standard (non-neural) processing and neural network processing. The electric controller (250) interfaces to and controls the lighting (248) and the electro-mechanical pruning mechanism (210), and
25 interfaces to the stereoscopic camera (249) to control its operation and to receive image data from it (249). The electro-mechanical pruning mechanism (210) has a workpiece positioner (225) which holds and positions the workpiece (100) (*i.e.*, the bud or other pruning target or harvest fruit), a cutting tool (220), a cutting tool positioner (230), and a cutting tool operator (240).

30 FIG. 2 shows an orthographic view of a preferred embodiment of the electro-mechanical pruning apparatus (210). The pruning apparatus (210) has a bed (215) on

which is mounted the workpiece positioner (225), the tool operator (240), and the tool positioner (230). Mechanically interfaced to the tool operator (240) and the tool positioner (230) is the cutting tool (220), which in the preferred embodiment is a scissors. The workpiece positioner (225) includes a gripping mechanism (not visible in FIG. 2) which can grip and release the workpiece (100). For purposes of the present exposition, the x axis is horizontal and the y axis is downwards, as is shown in FIG. 2. The workpiece positioner (225) is controlled by the electric controller (250) to produce rotation of the workpiece (100). According to the preferred embodiment, the workpiece (100) is gripped so that it is rotatable along an axis (that will be referred to as the z axis (226)) by the workpiece positioner (225) about what is roughly the longitudinal axis of the workpiece (100), and translatable along the x and y axes. The tool positioner (230) controls the position and orientation of the cutting tool (220). In particular, the tool positioner (230) has a tool positioner base (231) and a strut (232) extending therefrom, the strut (232) being pivotably connected to the cutting tool (220) at the tool operator (240). The protrusion distance of the strut (232) from the tool positioner base (231) is controlled by the electric controller (250). Causing the strut (232) to protrude or retract causes the cutting tool (220) to move outwards or inwards, respectively, relative to the base (231) and work product (100). The tool operator (240) also functions as an orientation control mechanism which can rotate the cutting plane of the cutting tool (220) about the x axis (where the angular displacement about the x axis from a plane parallel to the x - y plane is θ), and can rotate the cutting plane of the cutting tool (220) about the y axis (where the angular displacement about the y axis from a plane parallel to the x - y plane is Ω). Connecting the tool positioner base (231) to the bed (215) is a pivot mechanism (236) controlled by the electric controller (250). The pivot mechanism (236) rotates the tool positioner base (231) in a vertical plane by a small distance so the cutting tool (220) can engage with the workpiece (100). Given the control of the orientation of the workpiece (100) by the workpiece positioner (225), and control of the position of the cutting tool (220) by the tool positioner base (230), the cutting tool (220) can cut the workpiece (100) at any location on the workpiece (100) and at any orientation relative to the workpiece (100).

Extending vertically from the bed (215) is a span structure (260) having two side legs (262) and a crossbar (261). Mounted near the center of the crossbar (261) is a stereoscopic camera (249) having a left monoscopic camera (249a) and a right monoscopic camera (249b). The left monoscopic camera (249a) is oriented so as to be viewing directly down on the workpiece (100), *i.e.*, the center of viewing of the left monoscopic camera (249a) is along the y axis. Therefore, the right monoscopic camera (249b) is oriented so as to be slightly offset from viewing directly down on the workpiece (100). To each side of the stereoscopic camera (249) are lights (248) which are oriented to illuminate the workpiece (100) with white light. The white light is produced light emitting diodes (LEDs) which at least produce light in the red, green and blue frequency ranges.

FIG. 3A shows the pruning process (300) according to the preferred embodiment of the present invention. Once the workpiece (100) is placed (310) in the workpiece positioner (225), the stereoscopic camera (249) photographs the workpiece (100) to produce left and right camera image data (having reference numerals (401a) and (401b), respectively, in FIG. 4) which is collected (315) by the electric controller (250). The electric controller (250) extracts (320) depth, texture and color information from the image data (401a) and (401b) to produce a depth image (420), texture threshold image (445), and posterized color image (480) (as depicted in FIG. 4 and discussed in detail below). The depth image (420), texture threshold image (445) and posterized color image (480) are fed to the neural network (500), shown in FIG. 5 and discussed in detail below, and the neural network (500) utilizes those images (420), (445) and (480) to determine (325) the pruning operations on the workpiece (100) necessary to remove low resin-density areas. The electric controller (250) then prunes (330) the low resin-density areas according to the operations determined by the neural network (500). Once the pruning operations (330) have been performed, it is determined (335) whether all sides of the workpiece (100) have been pruned. If so (336), the pruning process (300) is complete (345). If not (337), the workpiece (100) is rotated (340) by a rotation increment by the workpiece positioner (225), and the process returns to the collection (315) of left and right image data (401a) and (401b). The rotation increment is the width of the swath which the cutting tool (220) can cut on the workpiece (100) (without rotation of the

workpiece (100) by the workpiece positioner (225)), which in the preferred embodiment is roughly 1 cm.

FIG. 3B shows the process (350) used to train the neural network (500) utilized in the pruning process (300) of FIG. 3A. The process begins with a workpiece (100) being placed (360) in the workpiece positioner (225). The stereoscopic camera (249) photographs the workpiece (100) to produce left and right camera image data (401a) and (401b) which is collected (365) by the electric controller (250). The electric controller (250) extracts (370) depth, texture and color information from the image data (401a) and (401b) to produce the depth image (420), texture threshold image (445), and posterized color image (480) as discussed in detail below in conjunction with FIG. 4. The depth image (420) and texture threshold image (445) are fed to the neural network (500), which is shown in FIG. 5 and discussed in detail below. A human trainer examines the workpiece (100) to locate low resin-density foliage and directs (375) the tool positioner (230) and the tool operator (240) to prune away the low resin-density areas. The details of where the human trainer has executed pruning are also fed to the neural network (500) for use in the training (377) of the neural network (500) as described below in conjunction with the description of the neural network (500) of FIG. 5. Utilizing the training information from the human trainer and the depth image (420) and texture threshold image (445), the neural network (500) is trained (377) using back propagation, as is well known in the art and described in detail in “Neural Networks for Pattern Recognition” by Christopher M. Bishop, Oxford University Press, England, 1995, which is incorporated herein by reference. Then it is determined whether the weights (which are labeled with 530-series reference numerals in FIG. 5 and will be referred to collectively with the reference numeral “530”) of the synapses (which are labeled with 520-series reference numerals in FIG. 5 and will be referred to collectively with the reference numeral “520”) have converged sufficiently to produce an “error rate” (which is defined as the difference between the current neural network’s training output and the labeled test data) which is below a predetermined value to consider the neural network (500) trained, as is described in detail below in conjunction with the description of FIG. 5. If the neural network weights (530) have converged (381), the training process (350) is ended. If the neural network weights (530) have not converged (382), then it is

determined (385) whether all sides of the workpiece (100) have been pruned. If not (387), then the workpiece (100) is rotated (390) by the workpiece positioner (225) by a rotation increment (as described above in FIG. 3A). If so (386), then another workpiece (100) is put (360) in the workpiece positioner (225), and the process continues as
5 described above.

FIG. 4A shows the stages of image processing (400) of the workpiece (100) according to the preferred embodiment of the present invention to create the depth image (420) and texture threshold image (445) which are fed to a neural network (500) (which is shown in FIG. 5 and discussed in detail below) to determine which low resin-density
10 areas should be removed. In particular, the stereoscopic camera (249) photographs the workpiece (100) to produce left camera image data (401a) and right camera image data (401b), which is sent to the electric controller (250). For each pair of camera images (401a) and (401b) the electric controller (250) generates a disparity image (410) which is a grey-scale image where the spatial disparity between each point on the workpiece (100)
15 as viewed by the left and right cameras (249a) and (249b), respectively, is reflected in the degree of whiteness of the associated pixel, with closer areas on the workpiece (100) being more white and farther areas being more black. More particularly, the disparity image (410) is produced by the application of intrinsic and extrinsic matrices, where the extrinsic matrix calculations correct for imperfections in the optics, and the intrinsic
20 matrix calculations determine depth based on the differences in the two images. The electric controller (250) converts the disparity image (410) to a depth image (420) by (i) converting the 8-bit integer disparity values from the disparity image (410) to a floating point number representing the distance of that point on the workpiece (100) from a ground plane in millimeters, where the ground plane is a plane which is located behind
25 the workpiece (100) and is parallel to the x - z plane, and (ii) mapping color information from the left stereo camera (401a) onto the depth information. Mapping the color information onto the depth information allows for easy and rapid visual verification of the accuracy of the depth determination process. A monochromatic grey-scale version of the left camera image (401a) is fed to the neural network (500).

30 The resin droplets at the tips of the trichomes have a maximum diameter of about 120 microns, and the hairs have a maximum height of about 135 microns. The preferred

embodiment of the present invention therefore determines texture on a characteristic texture length scale δ of approximately 0.2 mm to determine regions of high and low trichome (and therefore cannabinoid) density.

As also shown in FIG. 4A, a thresholded texture image (445) derived from the left and right camera images (401a) and (401b) is fed to the neural network (500). The thresholded texture image (445) shows areas of high and low smoothness on the characteristic texture length scale δ of 0.2 mm. The thresholded texture image (445) is generated by processing the left and right camera images (401a) and (401b) to produce a grey scale image (430) representing the roughness on the length scale of 0.2 mm through the application of a cross-correlation filter, which according to the preferred embodiment of the present invention is a Gabor correlation filter. The grey scale image (430) has 8-bit resolution where the rougher the region on the length scale of trichomes, the whiter the region. Smooth areas (*i.e.*, areas with few surface features, such as no trichomes) show as black, and areas with closely-spaced trichomes show as white. Next, edges are determined by taking the Laplacian (*i.e.*, the spatial divergence of the gradient of the pixel values) of the grey scale image (430) to generate an edge image (435). The edge image (435) shows the edges of the regions of high trichome density irrespective of illumination, *e.g.*, irrespective of whether a region is shadowed, since it is dependent on derivatives, in this case second derivatives. Of possible derivatives, the Laplacian has the advantage of naturally providing a field of scalars which is invariant under coordinate rotations and translations. The enlarged view of the edge image (435) provided in FIG. 4 shows a grey-scale image, although at a higher resolution the image (435) would be a complex, topological map-like image of closely-spaced curvy lines. The edge image (435) is then blurred over a length scale of a small multiple n of the characteristic texture length scale δ by convolution of the edge image (435) with a Gaussian with a width of $n\delta$ to provide a texture blur image (440), where the multiple n is preferably a relatively small, odd number such as 3 or 5. The greater the density of edges, the more white lines will appear in an area, and upon blurring the whiter that area will appear in the texture blur image (440). The texture blur image (440) is then thresholded by the application of a step function to provide a texture threshold image (445) where white areas correspond to areas with a density of trichomes above a threshold amount and black areas correspond

to areas with a density of trichomes below a threshold amount. The texture threshold image (445) is directed to the neural network (500).

As also shown in FIG. 4A, a posterized color image (480) derived from the left and right camera images (401a) and (401b) is fed to the neural network (500). The posterized color image (480) is a low color-resolution picture of the green areas of the left camera image (401a). The lights (248) illuminate the workpiece (100), as shown in FIGS. 1 and 2 and discussed above, with white light. The stereoscopic camera (249) feeds the image data for the left and right camera images (401a) and (401b) to the electric controller (250) which performs a hue-saturation-value spectral analysis on the image data (401a) and (401b) to produce a spectrum separation image (450) to locate areas reflecting green light, *i.e.*, light with wavelengths between 490 and 575 nm. Because the spectrum separation image (450) may show small specks of trichomes in areas that are not of high trichome density, for instance due to trichomes becoming dislodged from the workpiece (100) during handling, the next step is an erosioning to reduce such “speckle noise.” In particular, each green area in the spectrum separation image (450) is eroded by a single pixel along the circumference of the area (where a single pixel represents roughly a 0.2 mm x 0.2 mm area) to produce an erosion image (455). To restore non-noise areas to their original size, each green area is then dilated by adding a pixel-width line along the circumference of the green area to produce a dilation image (460). The colors in the dilation image (460) are then blurred by color averaging over an area which is preferably 3 or 5 pixels in width to produce a color blur image (465). The color blur image (465) – which is a grey scale representation of the greens -- is then thresholded via the application of a step function to the color blur image (465) to produce a black and white image (not depicted in FIG. 4A). The location of the step in the step function is a variable that may be under user control. Adjustment of the location of the step determines the thoroughness of the pruning of the workpiece (100). Setting the step location to a high value will bias the system towards ignoring small low resin-density areas, while setting the step location to a low value will bias the system towards pruning the smaller low resin-density areas. Then, convex hulls are created for each white area according to the process described below, and regions with a convex hull having an area

below a threshold size are discarded, *i.e.*, overwritten with black, to produce the color threshold image (470).

A set of points on a plane is said to be “convex” if it contains the line segments connecting each pair of its points, and the convex hull vertices are the vertices of the exterior line segments of the convex set. FIG. 6A shows an exemplary bud (100) with a stem (630), shade leaves (620) emanating from the stem (630), and sugar leaves (610) emanating from high-resin portions of the bud (100). FIG. 6A also shows the convex hull vertices (650) of the convex hulls which surround the stem (630), shade leaves (620), and sugar leaves (610). For clarity, FIG. 6B shows the convex hull vertices (650) without depiction of the bud (100) from which the convex hull vertices (650) were generated. It should be noted that convex hull vertices (650) of one object may meet the convex hull vertices of another object. For instance, in FIGS. 6A and 6B it can be seen that the convex hull vertices (650) of the shade leaves (620) meet each other, and the convex hull vertices (650) of the shade leaves (620) meet the convex hull vertices of the stem (630). From the convex hulls, the centroid, longitudinal axis, area, mean color, mean texture, and the standard deviation of the texture are calculated. As mentioned above, regions with a convex hull having an area below a threshold size are discarded, *i.e.*, overwritten with black, to produce the color threshold image (470). The other information computed from the convex hulls is also fed to the neural network (500) due to the usefulness of the information in, for instance, differentiating between leaves and stems.

To increase the amount of information in the image, the color threshold image (470) is combined with the green, blue and black color information from the original left camera image (401a) to produce an overlay image (475), where the blacks represent the low resin areas. Finally, the overlay image (475) is posterized to reduce the color palette, producing a posterized image (480) which is fed to the neural network (500). In particular, the posterizing process maps the spectrum of greens in the overlay image (475) to eight greens to produce the posterized image (475).

FIG. 5 shows a convolutional neural network (500) according to the preferred embodiment of the present invention for processing of the depth data (420) and texture data (445) to produce information required for pruning (330) of the low resin areas of the bud (100). The convolutional neural network (500) has an initial layer (510) which is the

input data (420), (445) and (480), a first feature map layer L1 (520), a second feature map layer L2 (530), a third feature map layer L3 (540), a fourth feature map layer L4 (550), a neuron layer (560), and an output layer (570). The input layer L0 (510) is a 256 x 256 array of the depth and texture pixels (420) and (445), respectively, described with

reference to FIG. 4A above. The input data of the initial layer (510) undergoes a first set of convolution processes (515) to produce the feature maps of the first layer L1 (520), the feature maps of the first layer L1 (520) each undergo a second set of convolution processes (525) to produce the feature maps of the second layer L2 (530), etc. Each convolution process (515), (525), (535), and (545) has the form

$$L(n+1)[m, n] = b + \sum_{k=0, K-1} \sum_{l=0, K-1} V^{(n+1)}[k, l] L_n[m+k, n+l], \quad (1)$$

where $V^{(n)}$ is the feature map kernel of the convolution to generate the n^{th} convolution layer, and the convolution is over $K \times K$ pixels. Convolution is useful in image

recognition since only local data from the n^{th} layer L_n is used to generate the values in $(n+1)^{\text{th}}$ layer $L(n+1)$. A $K \times K$ convolution over an $M \times M$ array of image pixels will

produce an $(M-K+1) \times (M-K+1)$ feature map. For example, 257 x 257 convolutions (*i.e.*, $K = 257$) are applied (515) to the 512 x 512 depth, texture and color pixel arrays (420), (445) and (480) to provide the 256 x 256 pixel feature maps of the first layer L1 (520).

The values in the first neuron layer F5 (560) are generated (555) from the feature maps of the fourth convolution layer L4 (550) by a neural network mapping of the form

$$F5 = \Phi_5(\sum_{k=0, 31} \sum_{l=0, 31} W^{(5)}[k, l] L4[k, l]) \quad (2)$$

where $W^{(5)}[k, l]$ are the weights of the neurons (555) and Φ_5 is an activation function which typically resembles a hyperbolic tangent. Similarly, the outputs F6 (570) of the convolution neural network (500) are generated (565) by a neural network mapping of the form

$$F6 = \Phi_6(\sum_j W^{(6)}[j] F5[j]) \quad (3)$$

where $W^{(6)}$ are the weights of the neurons (555) and Φ_6 is an activation function which typically resembles a hyperbolic tangent. The values of the feature map kernels V and

weights W are trained by acquiring pruning data according to the process of FIG. 4B

described above and using back propagation, as is well known in the art and described in

detail in "Neural Networks for Pattern Recognition" by Christopher M. Bishop, Oxford University Press, England, 1995, which is incorporated herein by reference. The output

values F6 (570) are the pruning instructions which are sent by the electric controller (250) to control the tool positioner (230), tool operator (240), and workpiece positioner (225).

In particular, the tool position (230) is given x , y and z position coordinates and orientation angles for the cutting tool (220), and the workpiece positioner is given a z position coordinate and a θ orientation coordinate for each pruning operation (330).

Alternatively, a convolutional neural network may operate directly on an image of a workpiece without the separate texture and color analysis described above. Rather, the convolutional neural network may be trained by supervised learning to recognize areas to be trimmed. FIG. 7A shows a workpiece and FIG. 7B, when overlayed with the image of FIG. 9A, shows white regions which have been identified by a human to be foliage to be removed. Using many such pairs of images as shown in FIG. 7A and 7B, the convolution neural network of this embodiment of the present invention is trained to recognize foliage to be pruned and/or foliage to be harvested.

This embodiment of a convolution neural network (800) according to the present invention for processing an image of a workpiece (100) to identify regions of the workpiece (100) to be pruned is shown in FIG. 8, and Keras library code for the convolution neural network (800) is as follows (with line numbers in the left hand margin added for ease of reference):

```

1  x =Convolution2D(32, 3, 3, input_shape=(1, image_h_v, image_h_v),
2      activation='relu', border_mode='same', init='uniform')(input_img)
3  x =Dropout(0.2)(x)
4  x =Convolution2D(32, 3, 3, activation='relu', border_mode='same')(x)
5  x =MaxPooling2D(pool_size=(2, 2))(x)
6  x =Convolution2D(64, 3, 3, activation='relu', border_mode='same')(x)
7  x =Dropout(0.2)(x)
8  x =Convolution2D(64, 3, 3, activation='relu', border_mode='same')(x)
9  x =MaxPooling2D(pool_size=(2, 2))(x)
10 x =Convolution2D(128, 3, 3, activation='relu', border_mode='same')(x)
11 x =Dropout(0.2)(x)
12 x =Convolution2D(128, 3, 3, activation='relu', border_mode='same')(x)

```

```

13  x =MaxPooling2D(pool_size=(2, 2))(x)
14  x =UpSampling2D(size=(2, 2))(x)
15  x =Convolution2D(64, 3, 3, activation='relu', border_mode='same')(x)
16  x =Dropout(0.2)(x)
5   17  x =UpSampling2D(size=(2, 2))(x)
18  x =Convolution2D(32, 3, 3, activation='relu', border_mode='same')(x)
19  x =Dropout(0.2)(x)
20  x =UpSampling2D(size=(2, 2))(x)
21  x =Convolution2D(1, 3, 3, activation='relu', border_mode='same')(x)
10  22
23  model = model = Model(input=input_img, output=x)

```

Keras is a modular neural networks library based on the Python and Theano programming languages that allows for easy and fast prototyping of convolutional and recurrent neural networks with arbitrary connectivity schemes. Documentation for Keras, which for instance can be found at <http://keras.io/>, is incorporated herein by reference.

Each Convolution2D process (lines 1, 4, 6, 8, 10, 12, 15, 18, and 21) performs the function

$$L_{out}[m, n, q] = \Phi[\sum_{i=0, K-1} \sum_{j=0, K-1} \sum_{k=0, D} V^{(q)}[i, j, k] L_{in}[m+i, n+j, k]],$$

(4)

where L_{in} is an input data tensor, L_{out} is an output data tensor, $V^{(q)}$ is the q^{th} feature map kernel, and the convolution is over $K \times K$ pixels, and Φ is the activation function. The variables k and q are commonly termed the depths of the volumes $L_{in}[m, n, k]$ and $L_{out}[m, n, q]$, respectively. A $K \times K$ convolution over an $M \times M$ array of image pixels will produce L_{out} where $m = n = (M-K+1)$. For example, 3×3 convolutions (*i.e.*, $K = 3$) on a $512 \times 512 \times k$ input will produce a $510 \times 510 \times q$ output. Convolution is useful in image recognition since only local data from L_{in} is used to generate the values in L_{out} .

The input data (801) to the convolution neural network (800) is monoscopic image data taken by the stereoscopic camera (249). Each channel of the stereoscopic data is a 1280×1024 array of grey-scale pixels. Since the computational effort of convolution neural networks is proportional to the area of the processed image, the image

is divided into smaller sections (henceforth to be referred to herein as *image tiles* or *tiles*) and the tiles are operated upon separately, rather than operating on the entirety of the image, to provide a computational speed-up. For instance, dividing the 1280 x 1024 pixel image into 256 x 256 pixel tiles results in a speed-up by a factor of almost 20.

5 According to the preferred embodiment the tiles are 256 x 256 pixels and the image is tiled by a 4 x 5 array of tiles. Although reference numerals for the tiles are not utilized in FIGS. 7E, 7F, 7G and 7H, the 4 x 5 array of tiles is visible in the images of FIGS. 7E, 7F, 7G and 7H. In the text of the present specification tiles, generically and collectively, will be given the reference numeral “700.” While even smaller tiles (700) do result in a
 10 speed-up in the processing time, according to the present invention the image tiles (700) are not smaller than twice the characteristic width of the largest feature which must be identified by the convolution neural network (800). According to the preferred embodiment of the present invention, the tiles (700) have a width roughly equal to the widest of the shade leaves (620) of the marijuana bud (100), which is approximately 3
 15 cm. This characteristic width may, for instance, be determined by identifying the largest wavelengths in a Fourier analysis of the image, or by directly measuring the widths of shade leaves on a sample foliage. The input data is fed to a first convolution layer (802) which, as per the Convolution2D instruction on lines 1 and 2 of the Keras code provided above, uses 32 feature maps (as per the first argument of the instruction) of size 3x3 (as
 20 per the second and third arguments of the instruction) to perform convolution filtering. The input_shape argument specifies that there is one channel of input data, *i.e.*, grey-scale input data, and the height argument image_h_v and width argument image_h_v of the input image input_img, which is the size of an input image tile (700), is specified as 256 x 256 pixels. According to the present invention the image resolution is selected such
 25 that trichomes have a width of one or two pixels. The 3 x 3 feature maps can therefore function to detect areas which are rough on the length scale of trichomes. Additionally, these 3 x 3 feature maps function to detect edges of leaves and stems.

As per the activation argument of the Convolution2D instruction on line 2 of the Keras code provided above, the activation function Φ is a relu function. “Relu” stands
 30 for REctified Linear Unit and a relu function $f(x)$ has the form $f(x) = \max(0, x)$, *i.e.*, negative values of x are mapped to a zero and positive values of x are unaffected. The

size of the input tile (700), feature map dimensions (*i.e.*, 3 x 3), and step size (which by default, since no step size is specified, is unity) are chosen such that no exceptional processing is required at the borders, so the setting of `border_mode='same'` indicates no special steps are to be taken. The values to which the weights of the 3x3 feature maps
 5 have been initialized by the `init` argument are 'uniform' *i.e.*, a white noise spectrum of random values.

As shown in FIG. 8, following the first convolution by the `Convolution2D` instruction (802) of lines 1 and 2 of the Keras code is a `Dropout` instruction (803) in line 3 of the Keras code. The argument value of 0.2 in the function `Dropout` means that the
 10 contribution of a randomly-chosen 20% of the values in an input data tensor L_{in} are set to zero on the forward pass and value updates are not applied to the randomly-chosen neurons on the backward pass. Dropout is a regularization technique for neural network models proposed by Srivastava, et al. in a 2014 paper entitled "Dropout: A Simple Way to Prevent Neural Networks from Overfitting," *Journal of Machine Learning Research*,
 15 15 (2014) 1929-1958, which is incorporated herein by reference. As per the title of the article, dropout is useful in preventing the large number of weights in a neural networking from producing an overfitting, thereby providing better functioning and more robust neural networks. By randomly removing neurons from the network during the learning process, the network will not come to rely on any subset of neurons to perform
 20 the necessary computations and will not get mired in the identification of easily identifiable features at the cost of neglecting features of interest. For instance, without the inclusion of `Dropout` instructions, the neural network of the present invention gets mired in identifying the black background and would not continue refinement of the weights so as to identify the features of interest.

25 Following the `Dropout` instruction (803), the convolution neural network performs a second convolution (804). As shown in line 4 of the Keras code provided above, the convolution again has 32 feature maps of size 3 x 3, a `relu` activation function, and the border mode is set to `border_mode='same'`. All other parameters of the second convolution (804) are the same as those in the first convolution (802). The output of the
 30 second convolution (804) is directed to a pooling operation (805) which, as shown in line 5 of the Keras code, is a `MaxPooling2D` instruction which outputs the maximum of each

2 x 2 group of data, i.e., for the 2 x 2 group of pixels in the k^{th} layer $L_{\text{in}}(m, n, k)$, $L_{\text{in}}(m+1, n, k)$, $L_{\text{in}}(m, n+1, k)$, and $L_{\text{in}}(m+1, n+1, k)$, the output is $\text{Max}[L_{\text{in}}(m, n, k), L_{\text{in}}(m+1, n, k), L_{\text{in}}(m, n+1, k), L_{\text{in}}(m+1, n+1, k)]$. The advantage of pooling operations is that it discards fine feature information which is not of relevance to the task of feature
 5 identification. In this case, a pooling with 2 x 2 pooling tiles reduces the size of the downstream data by a factor of four.

The output of the pooling operation (805) is directed to a third convolution filter (806). As shown in line 6 of the Keras code provided above, the convolution has 64 feature maps (instead of 32 feature maps as the first and second convolutions (802) and
 10 (804) had) of size 3 x 3, a relu activation function Φ and the border mode is set to `border_mode='same'`. All other parameters of the third convolution (806) are the same as those in the second convolution (804). The output of the third convolution (806) is directed to a second Dropout instruction (807) as shown in line 7 of the Keras code, and so on with the Convolution2D instructions of lines 8, 10, 12, 15, 18, and 21 of the Keras
 15 code corresponding to process steps 808, 810, 812, 815, 818 and 821 of FIG. 8, the MaxPooling2D instructions of lines 9 and 13 of the Keras code corresponding to process steps 809 and 813 of FIG. 8, and the UpSampling2D instructions of lines 14, 17 and 20 corresponding to process steps 814, 817 and 820 of FIG. 8.

The output of the pooling operation (813), corresponding to line 13 of the Keras
 20 code, is directed to an up-sampling operation (814), corresponding to the UpSampling2D instruction on line 14 of the Keras code. Up-sampling is used to increase the number of data points. The `size=(2,2)` argument of the UpSampling2D instruction indicates that the up-sampling maps each pixel to a 2x2 array of pixels having the same value, i.e., increasing the size of the data by a factor of four. According to the present invention the
 25 convolution neural network (800) of the present invention maps an input image of $N \times N$ pixels to a categorized output image of $N \times N$ pixels, for instance representing areas to be operated on by pruning and/or harvesting. Since poolings reduce the size of the data, and convolutions reduce the size of the data when the number of feature maps is not too large, an operation such as up-sampling is therefore needed to increase the number of neurons
 30 to produce an output image of the same resolution as the input image.

FIG. 10 shows the pruning process (1100) according to the preferred embodiment of the present invention. The process (1100) begins with the workpiece (or *target*) (100) being loaded (1105) in the workpiece positioner (1225) and translated and/or rotated into position (1110) for image capture (1115) using a stereoscopic camera (249). The stereoscopic camera which views the workpiece (100) has a left monoscopic camera (249a) and a right monoscopic camera (249b) as per FIG. 1. The left monoscopic camera (249a) is positioned and oriented so as to view directly down on the workpiece (100), *i.e.*, the center of viewing of the left monoscopic camera (249a) is along the z' axis of FIG. 12A. The right monoscopic camera (249b) is positioned and oriented so as to view the workpiece (100) but to be slightly offset from viewing directly down on the workpiece (100). Conceptually and computationally it is advantageous to utilize a center-line image and an offset image rather than two offset images, in part because according to the preferred embodiment the neural network (800) utilizes data from a single image. Also as shown in FIG. 1, to each side of the stereoscopic camera (249) are lights (248) which are oriented to illuminate the workpiece (100) with white light. The stereoscopic camera (249) photographs the workpiece (100) to produce center-line and offset camera image data which is collected by an electric controller (250).

The center-line image data is fed to the neural network (800) of FIG. 8 and the Keras code provided above, and the neural network (800) utilizes that data to determine (1125) the pruning locations on the workpiece (100) necessary to remove low trichome-density areas. According to the present invention the system includes a threshold trichome density setting. Regions with a threshold trichome density below the threshold trichome density setting are regions to be pruned. A determination (1135) is then made as to whether there are any pruning areas visible. If not (1136), then a determination is made (1140) as to whether the entire workpiece (100) has been inspected. If so (1142), then the workpiece (100) is unloaded (1150) and a next workpiece (100) is loaded (1105). If the entire workpiece (100) has not been inspected (1141), then the workpiece (100) is translated and/or rotated to the next position (1110).

While only the center-line image is fed to the neural network (800) for determination of the pruning locations on a two-dimensional image, both the centerline and offset image data are used to generate (1160) a three-dimensional surface map. If the

neural network (800) determines (1135) that pruning locations are visible (1137) on the workpiece (100), then the process flow continues with the combination (1165) of the three-dimensional surface map and the neural network-determined pruning locations. Areas to be pruned are selected (1170), and then the positions of the cutting tool (1000) necessary to perform the pruning operations are determined and the necessary cutting operations are performed (1175). Once the cutting operations have been performed (1175), the workpiece is translated or rotated (1110) to the next operations position. The rotation increment is the width of the swatch which the cutting tool (1000) can cut on the workpiece (100) (without rotation of the workpiece (100) by the workpiece positioner (1220)), which in the preferred embodiment is roughly 1 cm.

FIG. 11 shows the process (1200) used to train the neural network (800) utilized in the pruning process (800) of FIG. 8. The process begins with the collection (1205) of two-dimensional images. As mentioned above, according to the preferred embodiment stereoscopic images are utilized by the method and apparatus, but only monoscopic images are used for the training of the neural network (800). The stereoscopic camera (249) photographs the workpiece (100) to produce camera image data which is collected (1205) by the electric controller (250). For each image, a human trainer identifies (1210) regions on the workpiece (100) to be pruned or otherwise operated on. For instance, FIG. 7A shows an image of a marijuana bud (100) and FIG. 7B shows the regions 101a through 101m (collectively or generically to be referred to with reference numeral 101) identified by a human operator as regions of low cannabinoid density, and therefore regions to be pruned. In particular, FIG. 7A shows a marijuana bud (100) where the right half has been trimmed of shade leaves, and regions (101) in the image of FIG. 7B correspond to locations of the shade leaves.

The regions (101) identified by the human trainer are fed to the neural network (800) for training (1215) of the neural network (800) (as is described above in conjunction with the description of supervised learning of the neural network (500) of FIG. 5). Utilizing the training information from the human trainer, the neural network (800) is trained (1215) using back propagation, as is well known in the art and described in detail in “Neural Networks for Pattern Recognition” by Christopher M. Bishop, Oxford University Press, England, 1995, which is incorporated herein by reference. Then neural

network testing (1220) is performed by evaluating the error between the output generated by the neural network and the low-cannabinoid regions (101) identified by the human operator. If the error rate is below 1% (1226), then the neural network is considered to have converged sufficiently to be considered trained and the training process (1200) is complete (1230). If the neural network weights have not (1227) converged to produce an error rate of less than 1%, then the process (1200) returns to the neural network training step (1215) described above.

Images processed using this process (1200) are shown in FIGS. 7G and 7H. In particular, FIG. 7C shows an exemplary workpiece with many large shade and sugar leaves and FIG. 7D shows an exemplary workpiece with smaller shade and sugar leaves than those of the workpiece of FIG. 7C. Upon application of the above-described process (1200) upon the workpiece of FIG. 7C the image of FIG. 7G is produced. Similarly, upon application of the above-described process (1200) upon the workpiece of FIG. 7D the image of FIG. 7H is produced. As can be seen by comparison of FIG. 7C with FIG. 7G and comparison of FIG. 7D with FIG. 7H, the process (1200) has successfully produced images with white regions where the shade and sugar leaves are located.

Similarly, using a neural network of the specifications described above which is however trained to locate *high* trichome density regions, the image of FIG. 7E is generated from the image of FIG. 7C and the image of FIG. 7F is generated from the image of FIG. 7D. Inspection shows that FIG. 7E is roughly the complement to FIG. 7G, and FIG. 7F is roughly the complement to FIG. 7H. It should be noted that FIGS. 7E and 7F are presented herein for instructional purposes and according to the preferred embodiment of the present invention only regions of low trichome density are located by the neural network (800).

FIG. 12 shows a mechanical system (1300) for control of the cutting tool (1000) and workpiece (not visible in FIG. 12 but for the sake of consistency to be referred to with the reference numeral “100”) where the cutting tool (1000) can cut at any location on the workpiece (100) and at any angle. The electronic control system for operation of the mechanical system (1300) is not visible in FIG. 12, but such electronic control systems are well-known in the art of electronic control of stepper motors, brushless direct-current electric motors, brushed direct-current electric motors, servo motors, etc.

The position and orientation of the cutting tool (1000) is controlled by a cutting tool control system the mechanical portion of which includes a pair of vertical slide bars (1301) on which a chassis bar (1305) may be slideably positioned along the z' axis (according to the coordinate system shown at the top left). Motion of the chassis bar (1305) is produced by a stepper motor (not shown) connected to a control belt (1306) which is in turn connected to the chassis bar (1305). An inner arm (1310) is attached to the chassis bar (1305) via a first rotation mount (1315) which allows rotation of the inner arm (1310) in the $x'-y'$ plane. The inner arm (1310) is attached to an outer arm (1330) via a second rotation mount (1335) which allows rotation of the outer arm (1310) relative to the inner arm (1310) in the $x'-y'$ plane. According to the coordinate system shown next to the cutting tool (1000) in FIG. 12, which corresponds to the coordinate system shown next to the cutting tool (1000) in FIG. 9A, the cutting tool is rotatable about the z axis and can be pivoted in the $y-z$ plane and the $x-y$ plane. Preferably, the motors (not shown in FIG. 12) used to control the positions/orientations of the chassis bar (1305), inner arm (1310), outer arm (1330), and cutting tool (1000) are brushless direct-current (BLCD) motors due to their speed.

The workpiece (100) is gripped by a grip mechanism (1325) on the workpiece positioning mechanism (1320). Generally, the workpiece (100) will have a longitudinal axis oriented along the y direction. The grip mechanism (1325) is mounted on and controlled by a grip control unit (1340). The grip control unit (1340) can rotate the grip mechanism (1325) about the y' axis. The grip control unit (1340) is attached to two positioning rafts (1346) which are slideable in the $+y$ and $-y$ directions on grip positioning bars (1345), and grip positioning mechanism (1350) controls the position of the grip control unit (1340) along the y' axis via positioning rod (1351). Preferably, the motors (not shown in FIGS. 12A and 12B) used in the grip control unit (1340) and the grip positioning mechanism (1350) are brushless direct-current (BLDC) motors due to their speed.

FIG. 12B is a schematic side view of the carriage assembly (1360) for the mechanical grip mechanism (1325). The mechanical grip mechanism (1325) is connected to the grip control unit (1340) via a control shaft (1326). The grip control unit (1340) is mounted on a mounting bracket (1370), and the mounting bracket (1370) is

affixed to a mounting plate (1390) via a spacer (1385). The spacer (1385) provides play in the mounting bracket (1370) due to the flexibility of the material of the mounting bracket. A pressure sensor (1380) located under the end of the bracket (1370) on which the grip control unit (1340) is mounted therefore can measure vertical force applied to the grip mechanism (1325), such as via the workpiece (100) (not shown in FIG. ~~12A~~ 12B). The mounting plate (1390) is in turn mounted on a moveable base (1395).

Although not depicted in FIG. 12A, the apparatus includes a stereoscopic camera (249). Preferably, the stereoscopic camera (249) is located directly above the workpiece (100), or the optical path is manipulated, so that one lens provides a center-line image and the other lens provides an offset image. According to the preferred embodiment of the present invention the lenses of the stereoscopic camera (249) have physical apertures (rather than effective apertures that are created electronically), so the aperture can be made small enough to provide a depth of field of 5 to 10 cm at a range on the order of 1 meter. (Effective apertures created electronically generally have a depth of field of roughly 0.5 cm at a range on the order of 1 meter.)

For resinous plants, such as marijuana, pruning using a scissor-type tool can be problematic because resins accumulate on the blades and pivoting mechanism, adversely affecting operation and performance of the tool. According to the preferred embodiment of the present invention, the pruning tool is a heated, spring-biased scissor-type cutting tool. FIGS. 9A, 9B, and 9C show a top view, side view, and front view, respectively, of a heated, spring-biased scissor-type cutting tool (1000) according to a preferred embodiment of the present invention. The pruning tool (1000) has a fixed blade (1005) and a pivoting blade (1006). The fixed blade (1005) is integrally formed with a fixed arm (1007), and the pivoting blade (1006) is integrally formed with a pivoting arm (1008) of the tool (1000). The fixed blade (1005)/fixed arm (1007) is secured to a base plate (1040). The pivoting blade (1006)/pivoting arm (1008) is rotatable on a pivot mechanism (1020) having two nuts (1021) and (1022) mounted on a pivot screw (not visible in the figures). Mounted at the top of the pivot screw is a potentiometer (1030), the control dial (not visible) of the potentiometer (1030) being attached to the pivot screw such that rotation of the pivoting blade (1006) causes rotation of the pivot screw and the control dial of the potentiometer (1020). The resistance of the potentiometer (1020) -- as

controlled by the control dial -- is detected via electrical leads (1022) so that the position of the pivoting blade (1006) can be monitored. The end of the pivoting arm (1008) distal the pivot (1020) is connected to the control cable (1011) of a Bowden cable (1012). The housing (1010) of the Bowden cable (1012) is visible extending rightwards from the cutting tool (1000).

As is generally the case with scissor-type cutting tools, the roughly-planar faces of the blades (1005) and (1006) have a slight curvature (not visible in the figures). In particular, with reference to FIG. 9B, the downwards-facing face of the pivoting blade (1006) arcs from the pivot end to the end which is distal the pivot (1020) so that it is concave downwards, and the upwards-facing face of fixed blade (1005) arcs from the pivot end to the end which is distal the pivot (1020) so that it is concave upwards. These curvatures help insure good contact between the cutting edges of the blades (1005) and (1006) so that the tool (1000) cuts well along the entire lengths of the blades (1005) and (1006).

Attached to the base plate (1040) and connected to the pivoting arm (1008) is a bias spring (1015). According to the preferred embodiment, the bias spring (1015) is a formed wire which, at a first end, extends from the base plate (1040) in roughly the +z direction and has a U-shaped bend such that the second end of the bias spring (1015) is proximate the outside end of the pivoting arm (1008). The bias spring (1015) biases the pivoting arm (1008) upwards and such that the pivoting arm (1005) is rotated away from fixed blade (1006), *i.e.*, such that the cutting tool (1006) is in the open position. The play in the blades (1005) and (1006) provided by the pivot (1020) necessitates that the potentiometer (1030) be able to shift somewhat along the x and y directions, and rotate somewhat along the θ and ϕ directions. This play is provided by flexible mounting rod (1060) which is secured to and extends between the base plate (1040) and the potentiometer (1020).

The base plate (1040) is heated by a Peltier heater (not visible in the figures) secured to the bottom of the base plate (1040). The gel point of a polymer or polymer mixture is the temperature below which the polymer chains bond together (either physically or chemically) such that at least one very large molecule extends across the sample. Above the gel point, polymers have a viscosity which generally decreases with

temperature. Operation of the cutting tool (1000) at temperatures somewhat below the gel point is problematic because the resin will eventually accumulate along the blades (1005) and (1006) and in the pivot (1020) to an extent to make the tool (1000) inoperable. Cannabis resin is a complex mixture of cannabinoids, terpenes, and waxes which varies from variety to variety of plant, and hence the gel point will vary by a few degrees from variety to variety of plant. According to the preferred embodiment of the present invention, the tool (1000) is heated to at least the gel point of the resin of the plant being trimmed. Furthermore, with $v(T)$ being the viscosity v as a function of temperature T , and T_{gp} is the gel point temperature, preferably the tool is heated to a temperature such that $v(T) < 0.9 v(T_{gp})$, more preferably $v(T) < 0.8 v(T_{gp})$, and still more preferably $v(T) < 0.7 v(T_{gp})$. For cannabis, the tool (1000) is heated to a temperature of at least 32° C, more preferably the tool (1000) is heated to a temperature between 33° C and 36° C, and still preferably the tool (1000) is heated to a temperature between 34° C and 35° C.

According to an alternate embodiment of the present invention, the Peltier module is used for cooling, rather than heating, of the blades (1005) and (1006) of the cutting tool (1000). In particular, the Peltier module cools the blades (1005) and (1006) of the cutting tool (1000) to a temperature slightly above the dew point of water. Since resin becomes less sticky as its temperature decreases, the low temperature makes resin accumulation on the blades (1005) and (1006) less problematic. According to this preferred embodiment the control system for the Peltier module utilizes atmospheric humidity information to determine the temperature to which the blades (1005) and (1006) are to be cooled. Preferably, the blades (1005) and (1006) are cooled to a temperature below the wetting temperature of resin on the metal of the blades (1005) and (1006) and above the dew point of the moisture present in the atmosphere of the apparatus so that the resin does not flow into the pivot mechanism (1020).

Once the neural network (800) described above with reference to FIG. 8 determines regions of low trichome density, convex hulls (650) (as described above in reference to FIGS. 6A and 6B) are generated around regions of low trichome density according to the process (1400) shown in FIG. 13. The process (1400) utilizes the three-dimensional surface contour (1405) of the workpiece (100) determined by a depth analysis of the stereoscopic images from the stereoscopic camera (249), in combination

with the determinations of trichome density produced by the neural network (800) (such as the grey-scale images of FIGS. 7G and 7H). The grey-scale data is thresholded according to a user-controlled threshold, to create low trichome area contours (1410). The contours are converted (1415) into convex hulls (650), such as the convex hulls (650) shown in FIGS. 6A and 6B and described above. A set of points is said to be “convex” if it contains all the line segments connecting each pair of its points. The vertices of the convex hulls (650) are the vertices of the exterior line segments of the convex set. The convex hulls (650) are stored as hierarchical linked lists of vertices and for each convex hull (650) the enclosed area (based on a set of triangles spanning the vertices as per a Delvaney transform) of the convex hull (650) is computed. The convex hull (650) of greatest area which has not been processed is then found (1420) and for that convex hull (650) the number of vertices is converted (1425) to eight since (i) eight vertices can sufficiently well approximate convex polygons for the purpose of the present invention and (ii) for standard neural networks a fixed number of input points are required. If prior to conversion (1425) a convex hull (650) has more than eight vertices, then adjacent triplets of vertices are analyzed and center vertices of triplets which are most co-linear are discarded until there are eight vertices. If prior to conversion (1425) a convex hull (650) has less than eight vertices, then vertices are added between adjacent pairs of vertices which are separated by the greatest distance.

The eight-vertex convex hull output (1430) provided by the process of FIG. 13 is used as the input (1505) of the process (1500) shown in FIG. 14 for calculating and executing the tool positioning required to cut the foliage corresponding to the convex hull (650). The eight-vertex convex hull input (1505) is fed (1510) as eight 32-bit (x, y, z) coordinates to a tool-operation neural network which generates (1515) the tool position, the tool orientation, the distance between the tips of the blades (1005) and (1006) of the scissor-type cutting tool (1000), and the pressure applied by the blades (1005) and (1006) to the workpiece (100) (in the case of a “surface cut”) required to make a cut to remove the foliage corresponding to the eight-vertex convex hull (650). Keras code for a neural network used for the tool operation (1175) according to the present invention is provided below (with line numbers provided for ease of reference):

```

image_h = 8*3
image_v = 1
input_img = Input(shape=(1, image_h, image_v))
x = Convolution2D(32, 3, 1, input_shape=(1, image_h, image_v), activation='relu',
5 border_mode='same', init='uniform')(input_img)
x = Dropout(0.2)(x)
x = Convolution2D(32, 3, 1, activation='relu', border_mode='same')(x)
x = MaxPooling2D(pool_size=(2, 1))(x)
x = Convolution2D(64, 3, 1, activation='relu', border_mode='same')(x)
10 x = Dropout(0.2)(x)
x = Convolution2D(64, 3, 1, activation='relu', border_mode='same')(x)
x = MaxPooling2D(pool_size=(2, 1))(x)
x = Convolution2D(128, 3, 1, activation='relu', border_mode='same')(x)
x = Dropout(0.2)(x)
15 x = Convolution2D(128, 3, 1, activation='relu', border_mode='same')(x)
x = MaxPooling2D(pool_size=(2, 1))(x)
x = UpSampling2D(size=(2, 1))(x)
x = Convolution2D(64, 3, 1, activation='relu', border_mode='same')(x)
x = Dropout(0.2)(x)
20 x = UpSampling2D(size=(2, 1))(x)
x = Convolution2D(32, 3, 1, activation='relu', border_mode='same')(x)
x = Dropout(0.2)(x)
x = UpSampling2D(size=(2, 1))(x)
x = Convolution2D(1, 3, 1, activation='relu', border_mode='same')(x)

25 This neural network uses the same types of operations, namely Convolution2D, Dropout,
MaxPooling2D, and UpSampling2D, as used above in the neural network (800) shown in
FIG. 8. However, the input data, rather than being an image, is the eight three-
dimensional coordinates which form the vertices of a convex hull (650). Hence image_h
is set to a value of 24 and, since the data according to the present invention is processed
30 as a vector, image_v is set to 1. It should be noted that the “2D” moniker in the

```

Convolution2D, MaxPooling2D, and UpSampling2D operations are therefore somewhat misleading – the processing is a one-dimensional special case since image_v has been set to 1. Since the data is processed as a vector the feature maps of the Convolution2D operations are vector 3 x 1 feature maps. The neural network is human trained with pruning operations and the output of this neural network is three position coordinates (i.e., the (x, y, z) coordinates) of the cutting tool (1000), three angular orientation coordinates of the cutting tool (1000), the width the blades (1005) and (1006) of the cutting tool (1000) are to be opened for the pruning operation (1175), and the pressure to be applied by the cutting tool (1000) to the workpiece (100). Controlling the width of the blades (1005) and (1006) needed for cutting is useful in accessing foliage in crevices. The pressure is a useful parameter to monitor and control since this allows the cutting tool to perform “glancing” cuts where the cutting tool (1000) is oriented so that the blades (1005) and (1006) of the cutting tool (1000) rotate in a plane parallel to a surface plane of the workpiece (100). Then the blades (1005) and (1006) may be pressed against the workpiece (100) with pressure such that foliage protrudes through the blades (1005) and (1006) along a length of the blades (1005) and (1006). This is advantageous since glancing cuts are the most efficient way to prune some types of foliage.

Then using calculations well-known in the art of automated positioning, a collision-free path from the current position of the cutting tool (1000) to the position necessary to cut the foliage corresponding to the eight-vertex convex hull (650) is calculated. The cutting tool (1000) is then moved (1525) along the collision-free path and oriented and opened as per determination step (1515), and the cut is performed (1530). If foliage corresponding to all convex hulls (650) above a cut-off size have been pruned, then the pruning process is complete. However, if foliage corresponding to convex hulls (650) above the cut-off size remain, then the process returns to step (1420) to find the largest convex hull (650) corresponding to foliage which has not been pruned, and the process continues with steps (1425), (1430), (1505), (1510), (1515), (1520), (1525) and (1530) as described above.

Thus, it will be seen that the improvements presented herein are consistent with the objects of the invention described above. While the above description contains many specificities, these should not be construed as limitations on the scope of the invention,

but rather as exemplifications of preferred embodiments thereof. Many other variations are within the scope of the present invention. For instance: the neural network may include pooling layers; the texture may be categorized into more than just two categories (e.g., smooth and non-smooth) – for instance, a third category of intermediate smoothness
5 may be utilized; a grabbing tool may be substituted for the cutting tool if the apparatus is to be used for harvesting; the apparatus may have a grabbing tool in addition to the pruning tool; there may be more than one pruning tool or more than grabbing tool; there may be a deposit bin for harvested foliage; the apparatus may be mobile so as to enable pruning, harvesting, spraying, or other operations in orchards or fields; the lighting need
10 not be connected to the electric controller and may instead be controlled manually; the lighting may be a form of broad-spectrum illumination; the cutting tool need not be a scissor and, for instance, may instead be a saw or a rotary blade; the scissor may be more generally a scissor-type tool; the workpiece positioner may also pivot the workpiece by rotations transverse to what is roughly the longitudinal axis of the target; the texture length
15 scale may be based on other characteristics of the foliage, such as the length scale of veins or insects; neither stereo camera may be oriented with its center of viewing along the y axis – for instance, both stereo cameras may be equally offset from having their centers of viewing along the y axis; distance ranging may be performed using time-of-flight measurements, such as with radiation from a laser as per the JouleTM ranging
20 device manufactured by Intel Corporation of Santa Clara, California; viewing of electromagnetic frequencies outside the human visual range, such as into the infra-red or ultra-violet, may be used; the workpiece may not be illuminated with white light; the workpiece may be illuminated with LEDs providing only two frequencies of light; a color image, rather than a grey-scale image, may be sent to the neural network; a spring
25 mechanism need not have a helical shape; the neural network may be trained with and/or utilize stereoscopic image data; the error rate at which the neural network is considered to have converged may be greater than or less than what is specified above; etc.
Accordingly, it is intended that the scope of the invention be determined not by the embodiments illustrated or the physical analyses motivating the illustrated embodiments,
30 but rather by the claims.

CLAIMS

What is claimed is:

1. A method for use of a first convolutional neural network for determination of automated operations on a workpiece based on region classifications of said workpiece generated by said first convolutional neural network, said workpiece having first workpiece features of a first characteristic length scale and second workpiece features of a second characteristic length scale, said first characteristic length scale being larger than said second characteristic length scale, comprising:
 - generating a tiled image of said workpiece, said tiled image being an array of abutting tiles, a tile size of said tiles corresponding to a first distance on said workpiece being dependent on said first characteristic length scale, a separation between adjacent pixels in said tiles corresponding to a second distance on said workpiece being dependent on said second characteristic length scale;
 - providing pixel data of one of said tiles to an input of said first convolution neural network, said first convolution neural network having a first convolution layer utilizing a first number of first convolution feature maps, said first convolution feature maps having a first feature map size, said first convolution layer outputting first convolution output data used by at least one downstream convolution feature map to generate said region classifications.
2. The method of claim 1 wherein said number of said convolution feature maps is between 16 and 64.
3. The method of claim 1 wherein said feature map size is dependent on said second characteristic length scale.
4. The method of claim 1 wherein said second characteristic length scale is a peak in a Fourier analysis of an image of said workpiece.
5. The method of claim 4 wherein said peak in said Fourier analysis corresponds to a textural wavelength.
6. The method of claim 1 wherein said second distance is between 1 and 5 times said second characteristic length scale.

7. The method of claim 1 wherein said first workpiece features are leaves on said workpiece.
8. The method of claim 7 wherein said first workpiece features are leaves and said first characteristic length scale is a width of said leaves on said workpiece.
- 5 9. The method of claim 7 wherein said workpiece is marijuana foliage, said first workpiece features are shade leaves, said first characteristic length scale is a maximum width of said shade leaves, second workpiece features are marijuana trichomes, and said automated operations are prunings of low trichome density portions of said marijuana foliage.
- 10 10. The method of claim 9 wherein portions of said marijuana foliage having a trichome density below a trichome density threshold are subject to said prunings.
11. The method of claim 10 wherein said trichome density threshold is adjustable.
12. The method of claim 1 wherein said tile size is between 75% and 150% of said first characteristic length scale.
- 15 13. The method of claim 1 further including the step of converting said region classifications into a set of convex hulls such that regions within said convex hulls correspond to regions of said workpiece having a region classification level below a threshold level.
14. The method of claim 13 wherein said threshold level is adjustable.
- 20 15. The method of claim 13 further including the step of analyzing one of said convex hulls with a second neural network for determination of one of said automated operations.
16. The method of claim 15 further including the step of converting said convex hulls into convex hulls have a selected number of vertices.
17. The method of claim 16 wherein said selected number of vertices is eight.
- 25 18. The method of claim 1 further including the steps of:
- generating a stereoscopic image of workpiece, said stereoscopic image having a first image of said workpiece from a first angle and a second image of said workpiece from a second angle offset from said first angle,
- combining said stereoscopic image with said region classifications to produce
- 30 operations locations, and
- performing said automated operations based on said operations locations.

19. The method of claim 18 wherein said first image is a center line image, and said center line image is used to generate said tiled image.

20. An automated cutting tool for cutting a resinous plant, comprising:

a pivot having a pivot axis;

5 a fixed blade, said fixed blade having a first pivot end near said pivot and a first terminal end distal said first pivot end;

a rotatable blade mounted to said pivot and rotatable on said pivot about said pivot axis in a plane of rotation, said rotatable blade having a second pivot end near said pivot and a second terminal end distal said second pivot end, said rotatable blade being
10 rotatable on said pivot between an open position where said first and second distal ends are separated and a closed position where said fixed and rotatable blades are substantially aligned, said pivot providing translational play of said rotatable blade in said plane of rotation, said pivot providing rotational play of said rotatable blade about a longitudinal axis of said rotatable blade and about an axis orthogonal to said longitudinal axis of said
15 rotatable blade and said pivot axis;

a first biasing mechanism which biases said rotatable blade to said open position;

a second biasing mechanism which biases said second distal end of said rotatable blade orthogonal to said plane of rotation and in a direction of said fixed blade; and

a blade control mechanism for applying a force to rotate said rotatable blade
20 against said first biasing mechanism and towards said closed position.

21. The automated cutting tool of claim 20 further including a positioning monitoring mechanism for monitoring a displacement between the second distal end of said rotatable blade and said first distal end of said fixed blade.

22. The automated cutting tool of claim 02 wherein said positioning monitoring
25 mechanism is mounted on said pivot.

23. The automated cutting tool of claim 22 wherein said positioning monitoring mechanism is a potentiometer, a control dial of said potentiometer being connected to said pivot such that rotation of said rotatable blade rotates said control dial of said potentiometer.

24. The automated cutting tool of claim 20 wherein said first biasing mechanism and said second biasing mechanism are a single biasing spring.

25. The automated cutting tool of claim 20 further including a heater to heat said fixed and rotatable blades to a temperature above the gel point of resin of said resinous plant.

5 26. The automated cutting tool of claim 25 wherein said temperature is between 0.5° C and 3° C above said gel point of said resin.

27. The automated cutting tool of claim 20 further including a cooler to cool said fixed and rotatable blades to a temperature below the wetting temperature of resin of said resinous plant on the material of said fixed and rotatable blades and above the dew point
10 of atmospheric water.

28. The automated cutting tool of claim 27 wherein said temperature is between 0.5° C and 3° C above the dew point.

1/21

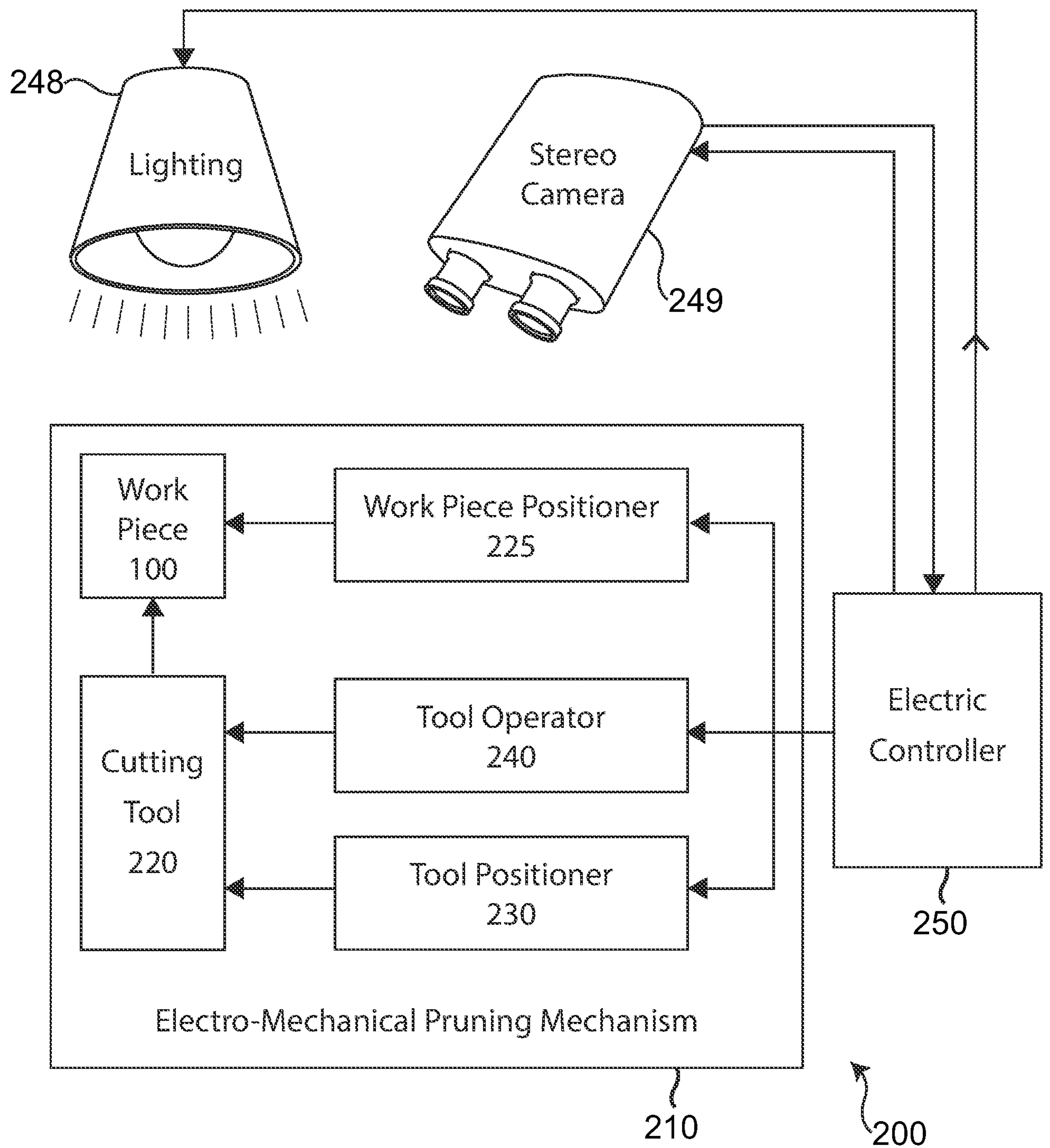


FIG. 1

2/21

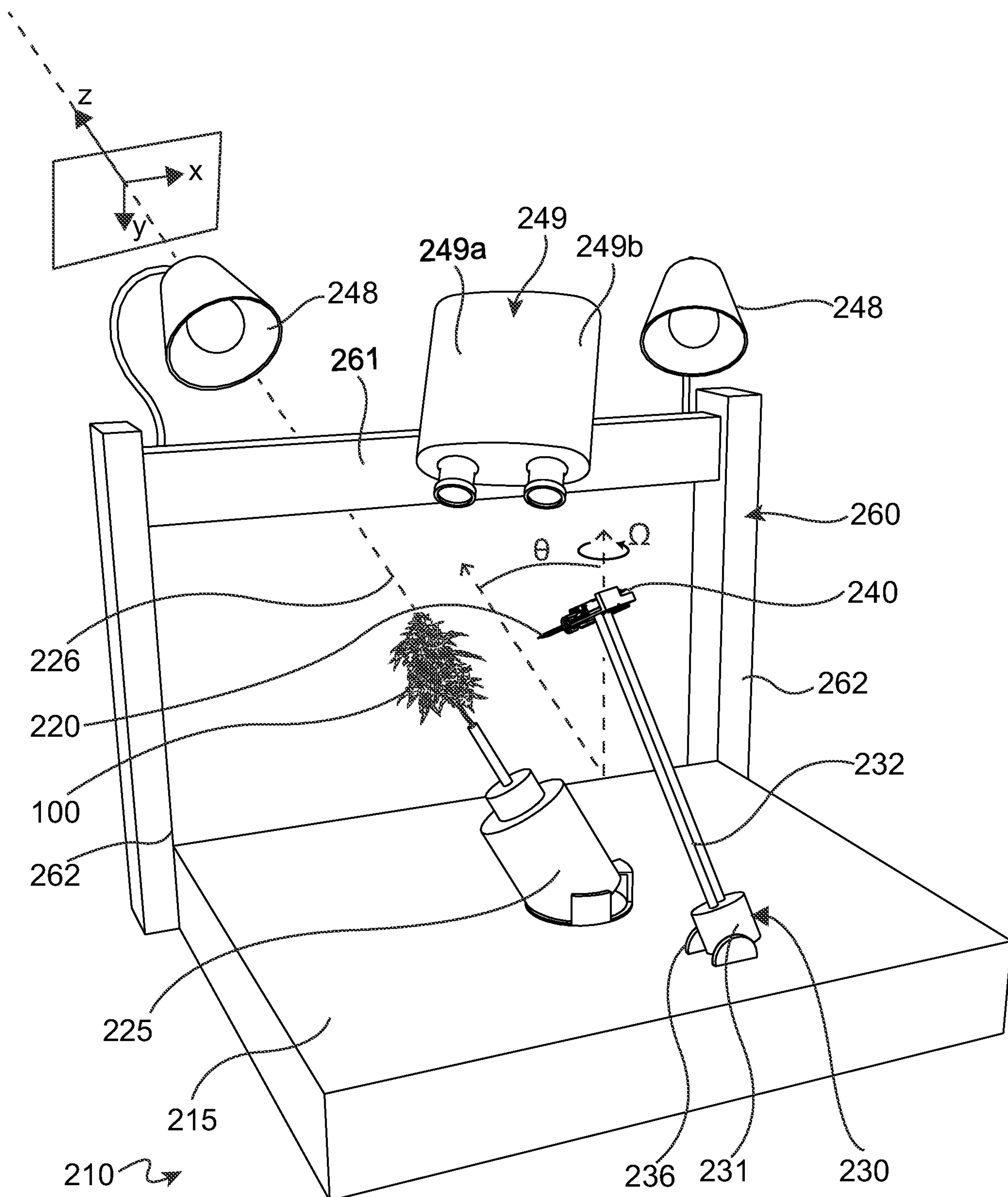
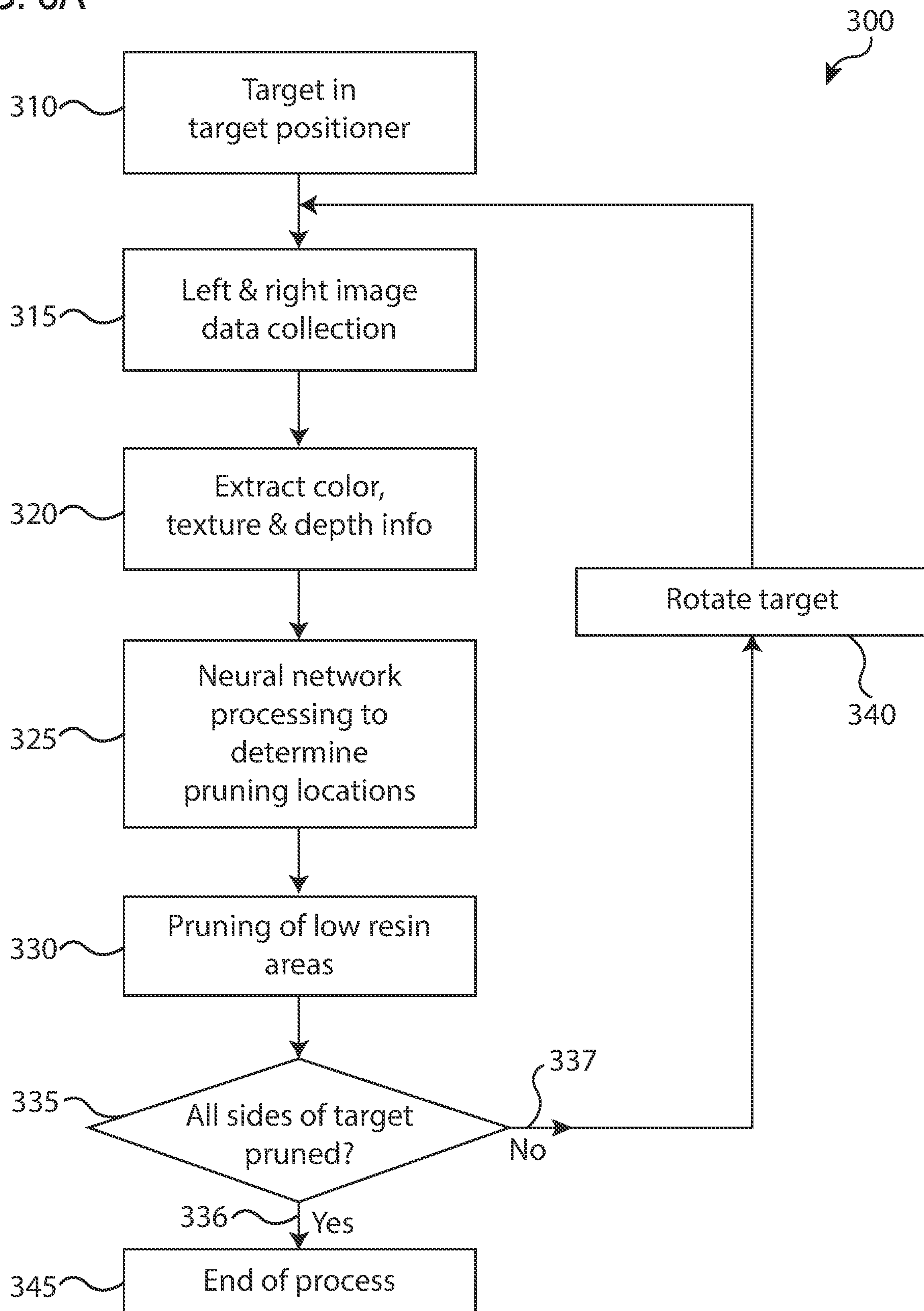


FIG. 2

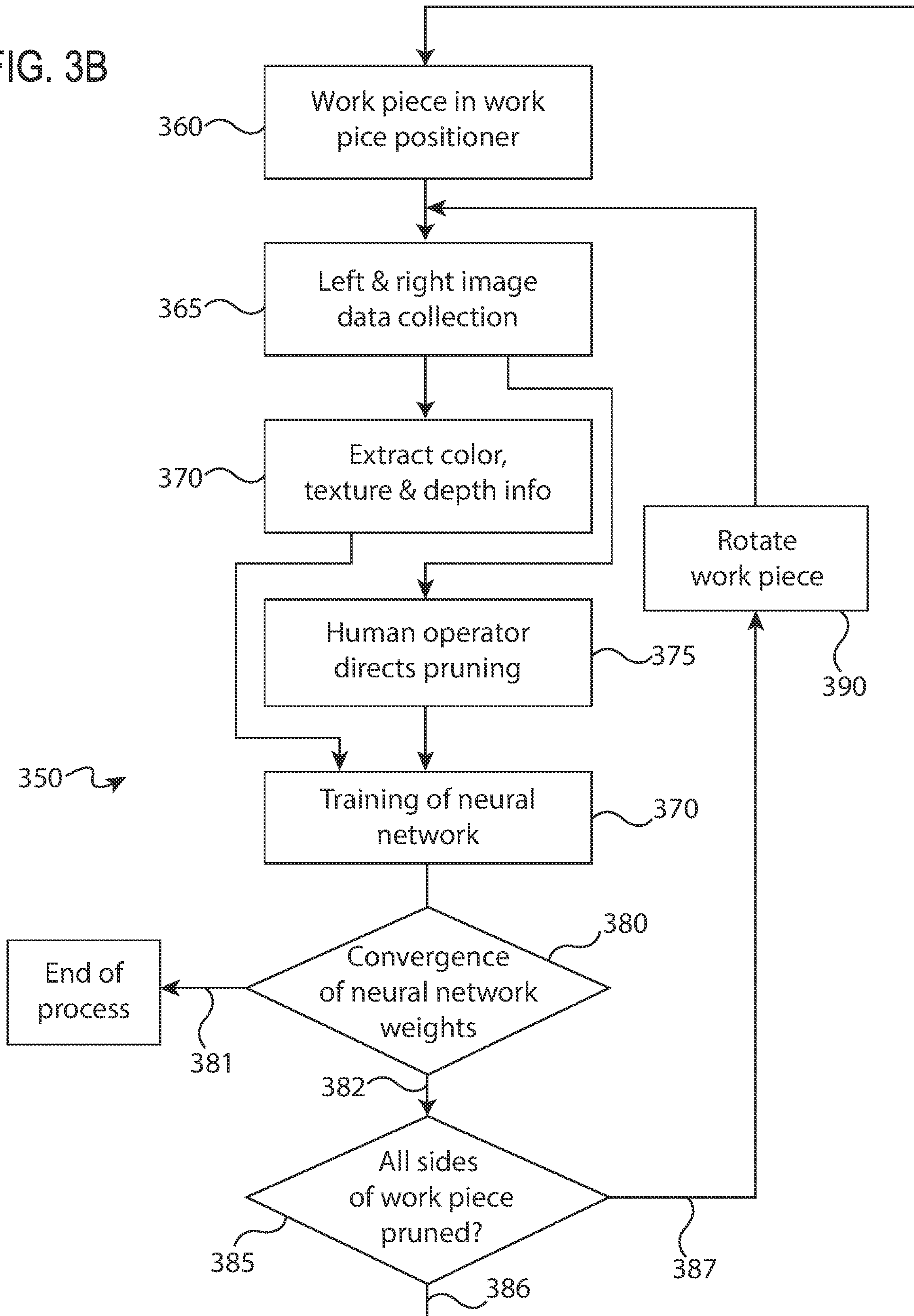
3/21

FIG. 3A



4/21

FIG. 3B



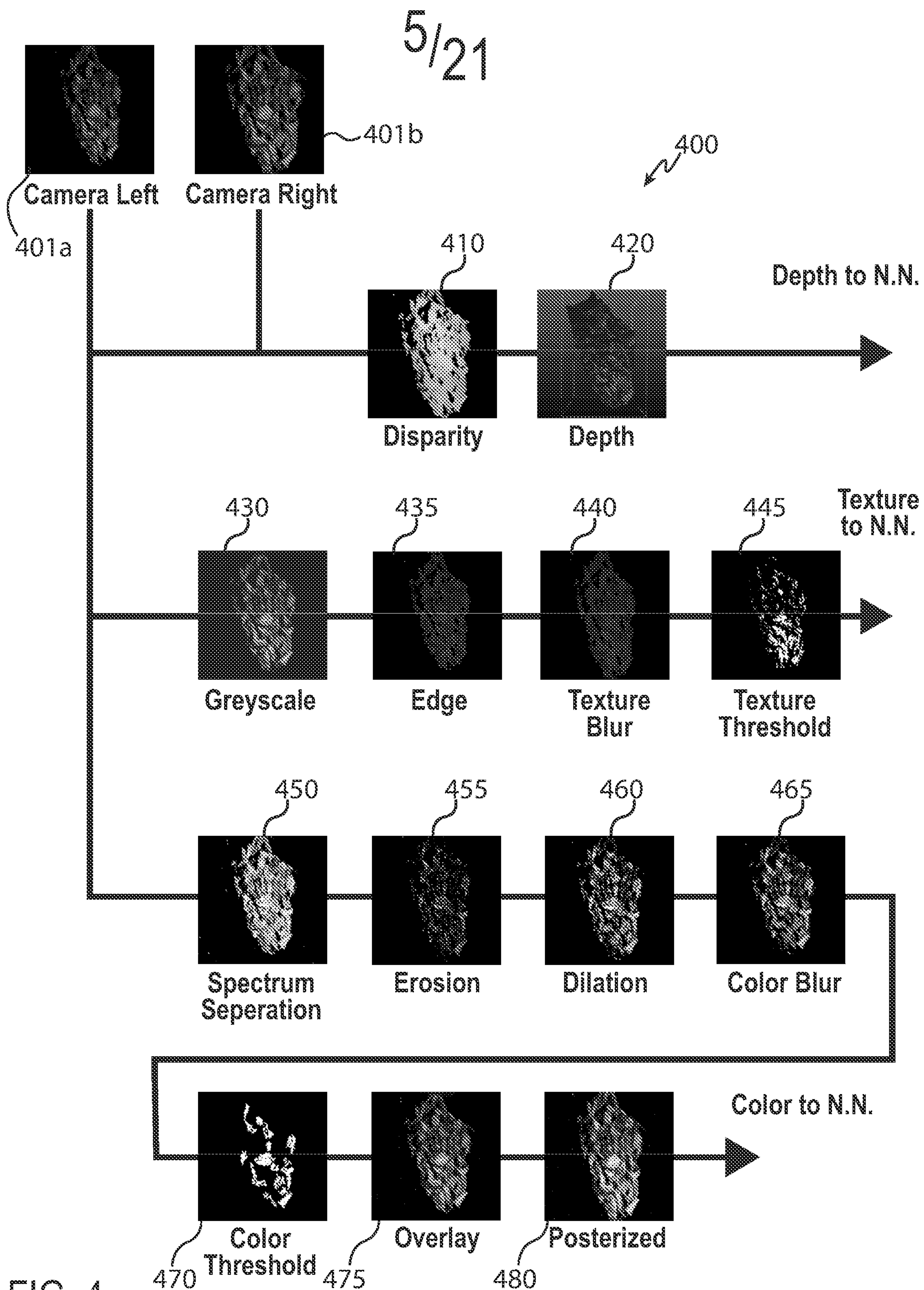


FIG. 4

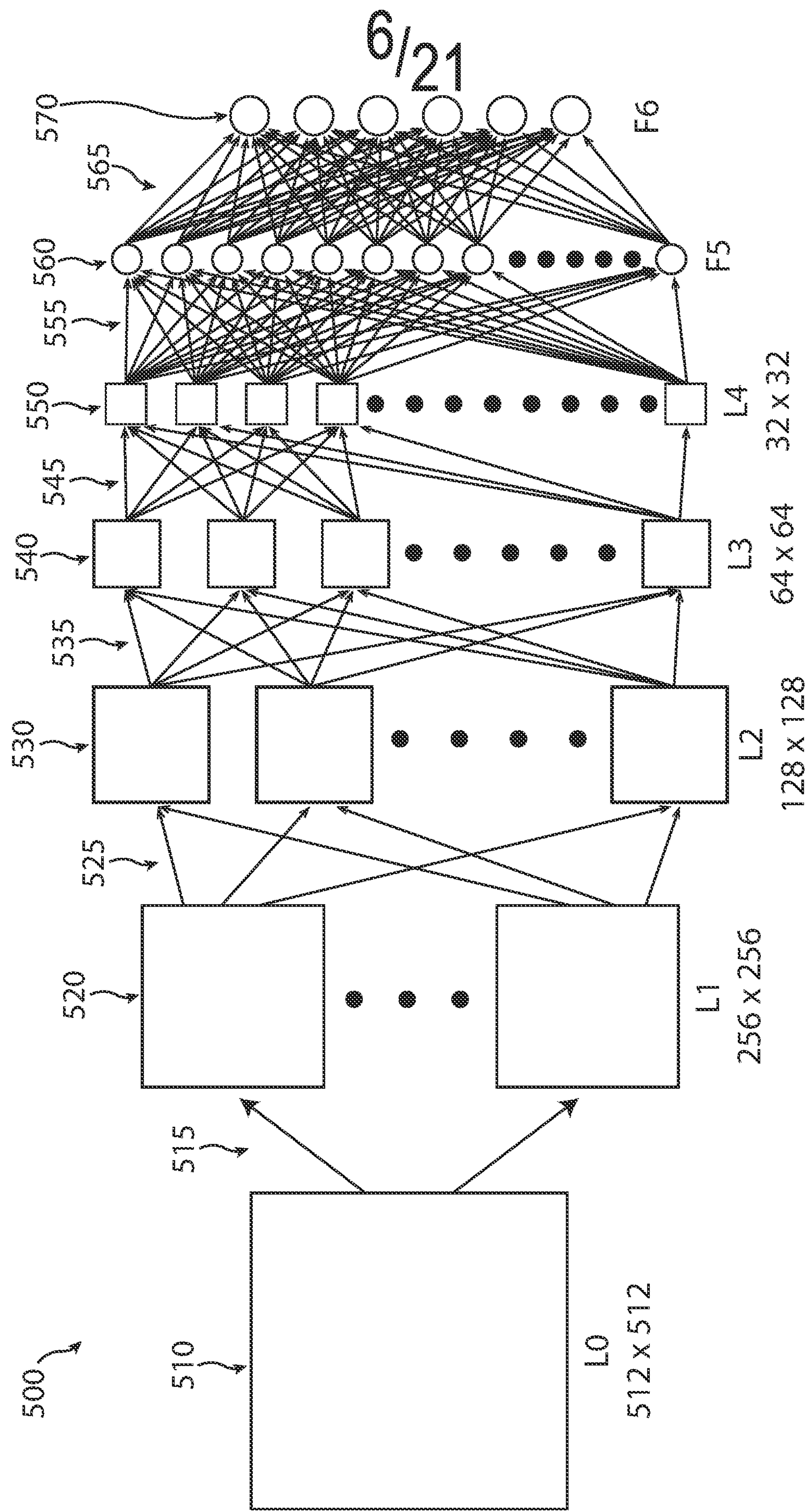


FIG. 5

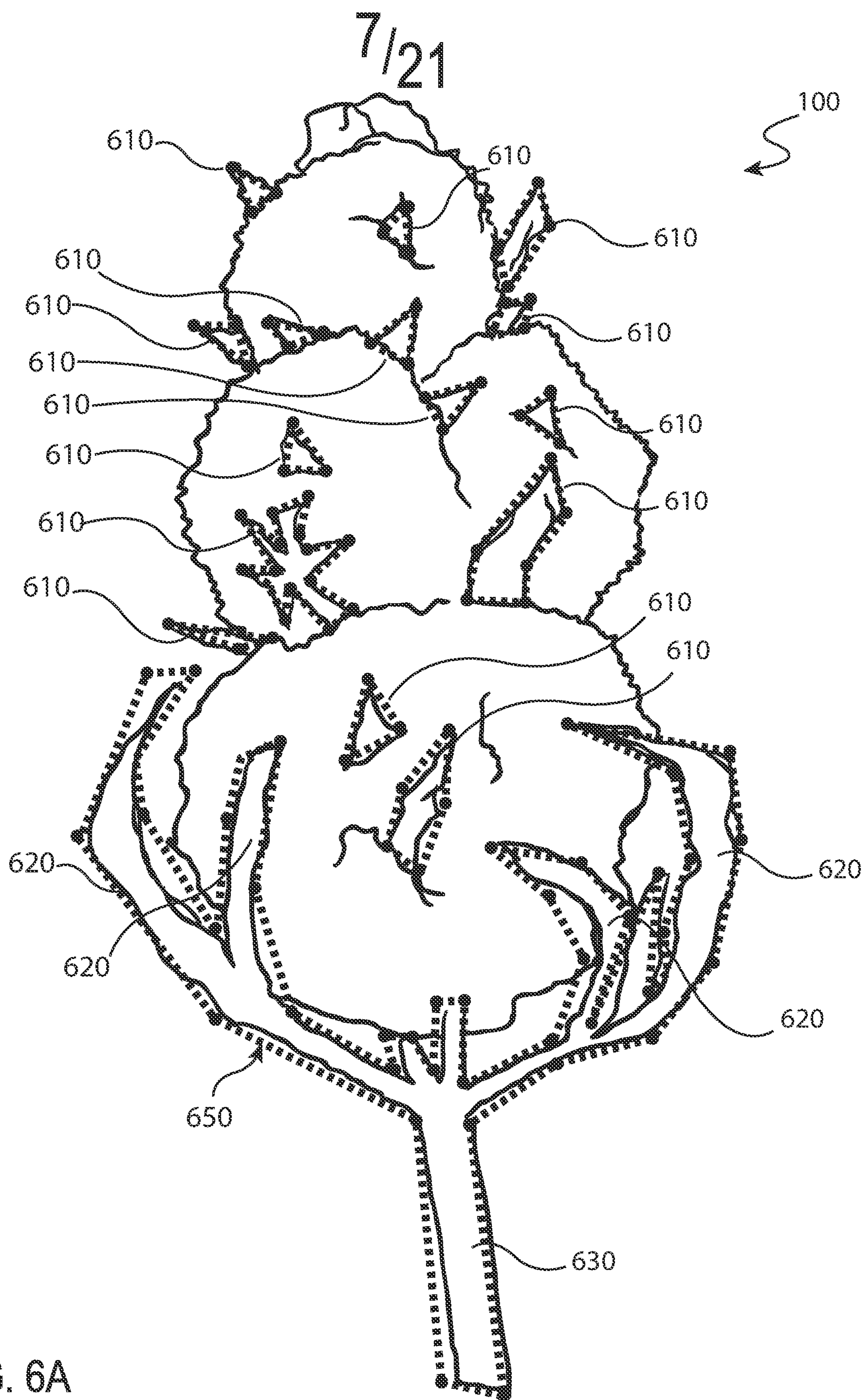


FIG. 6A

8/21

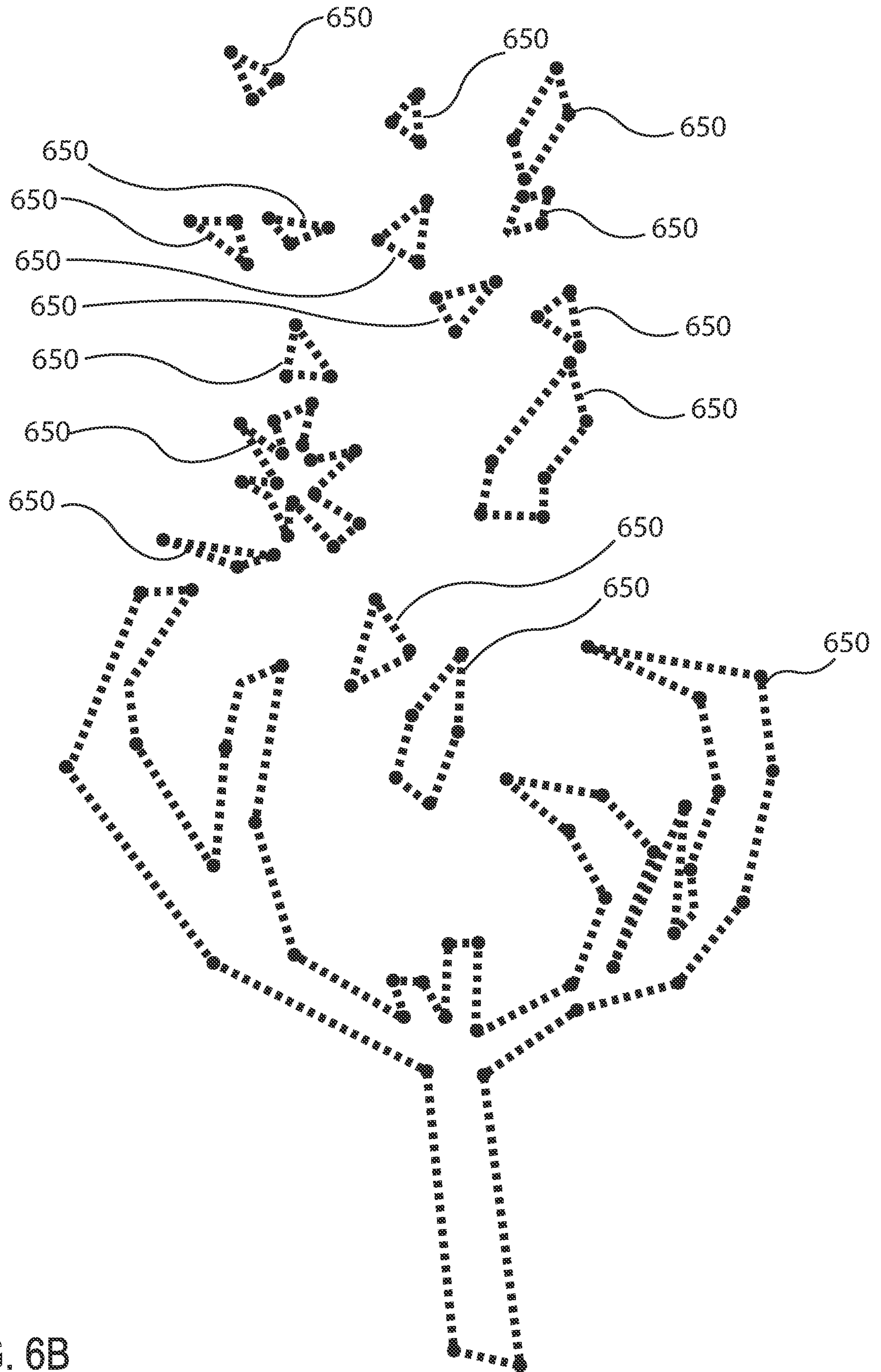


FIG. 6B

9/21



FIG. 7A

10/21

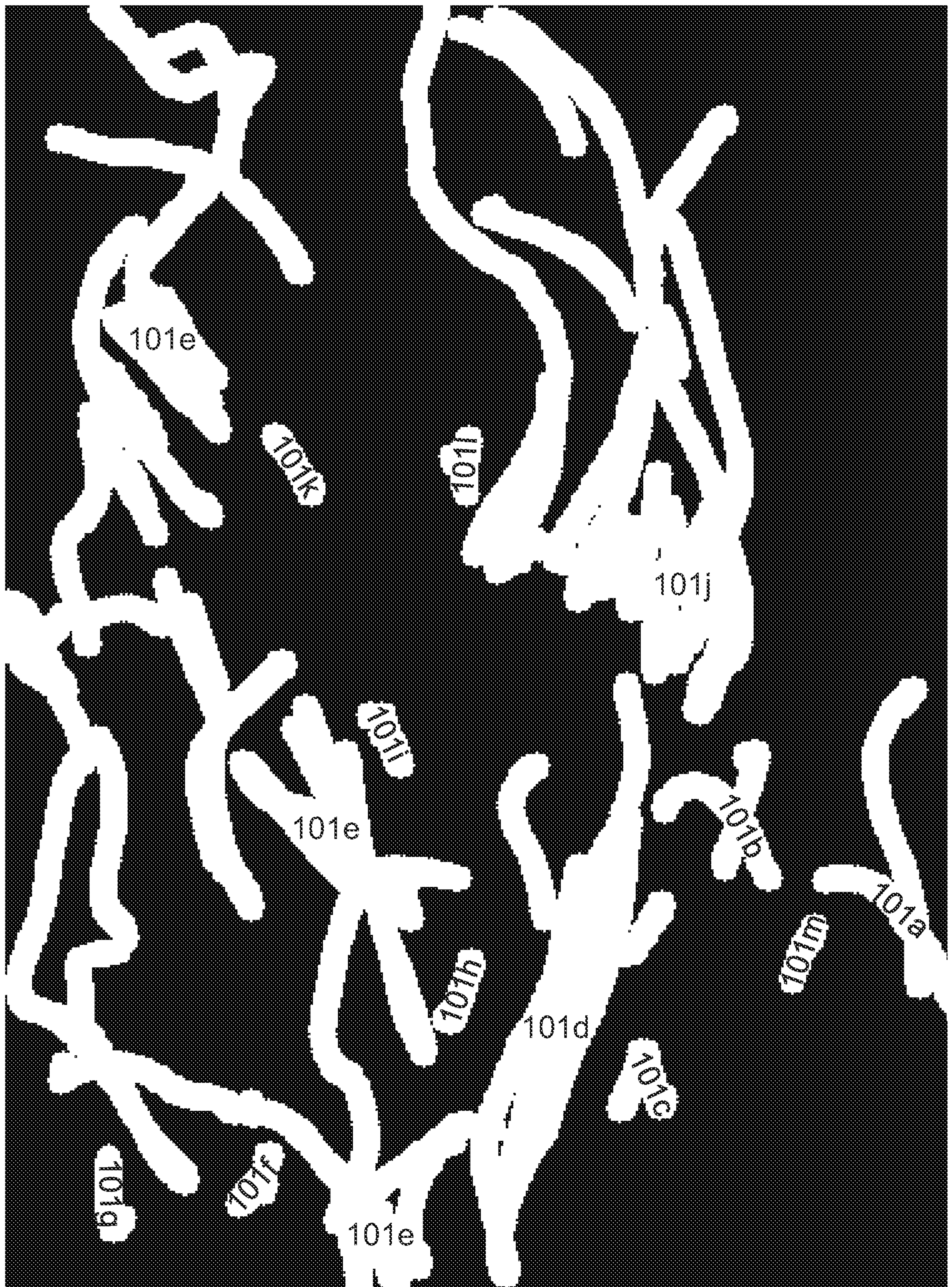


FIG. 7B

11/21



FIG. 7C

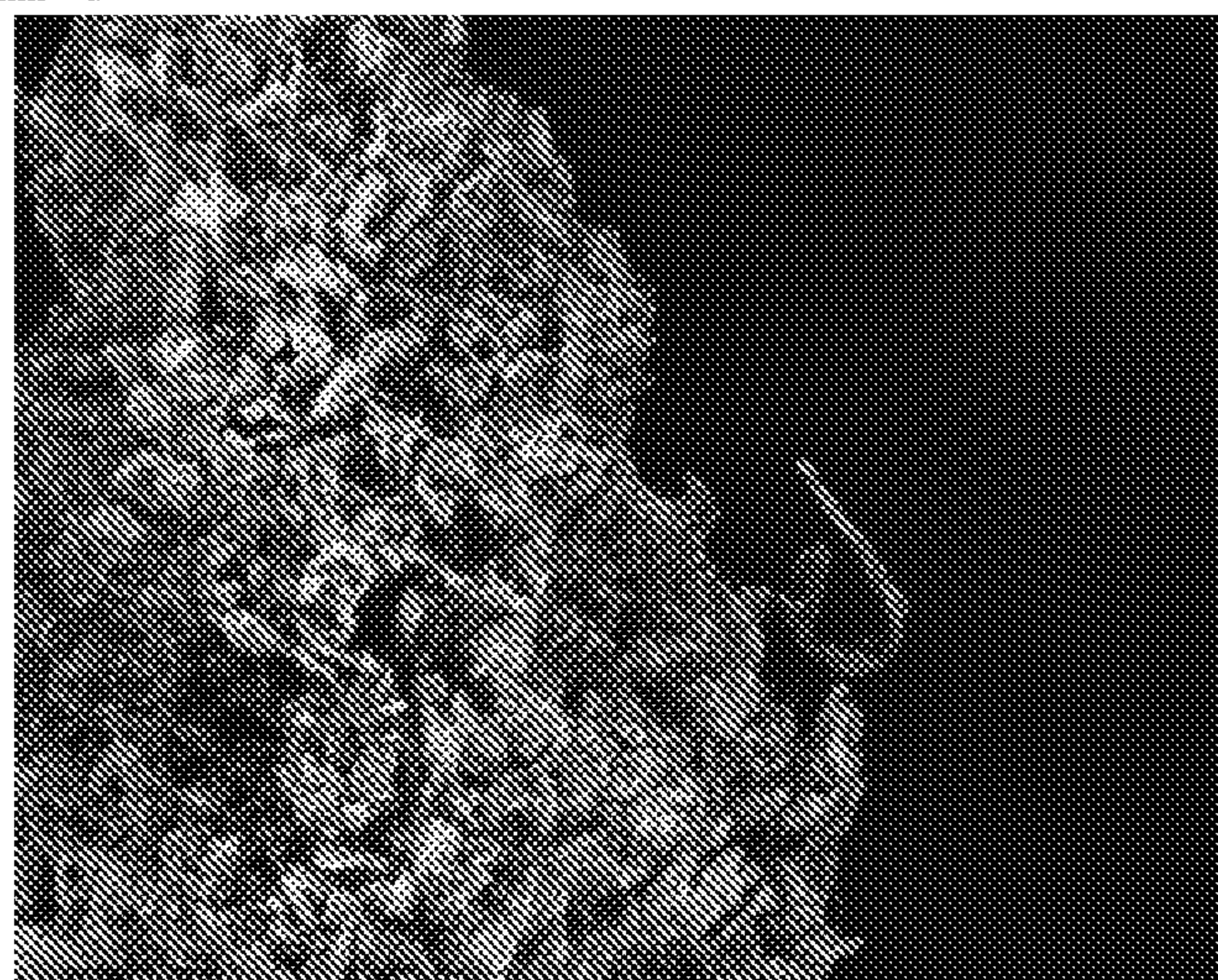


FIG. 7D



FIG. 7E

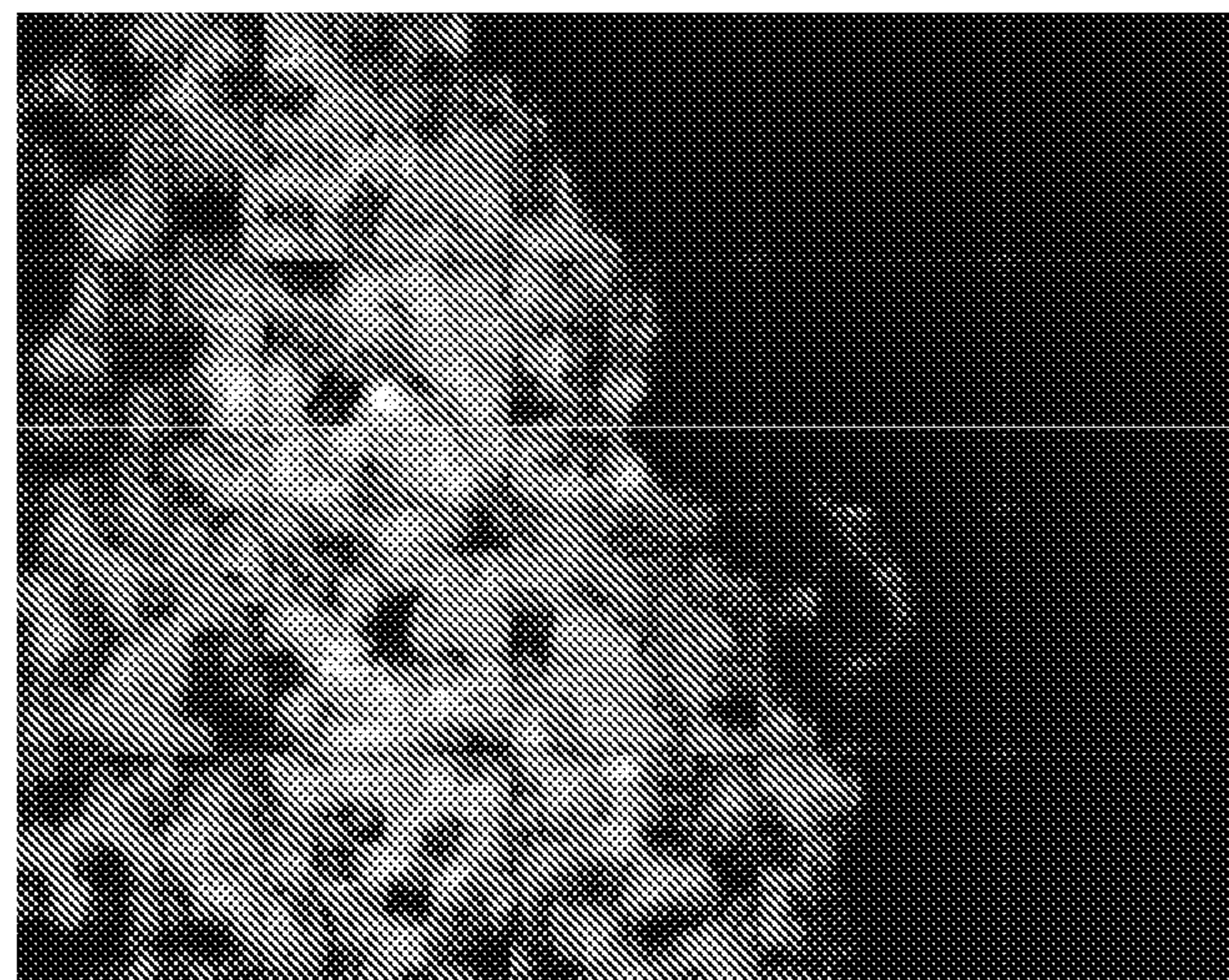


FIG. 7F

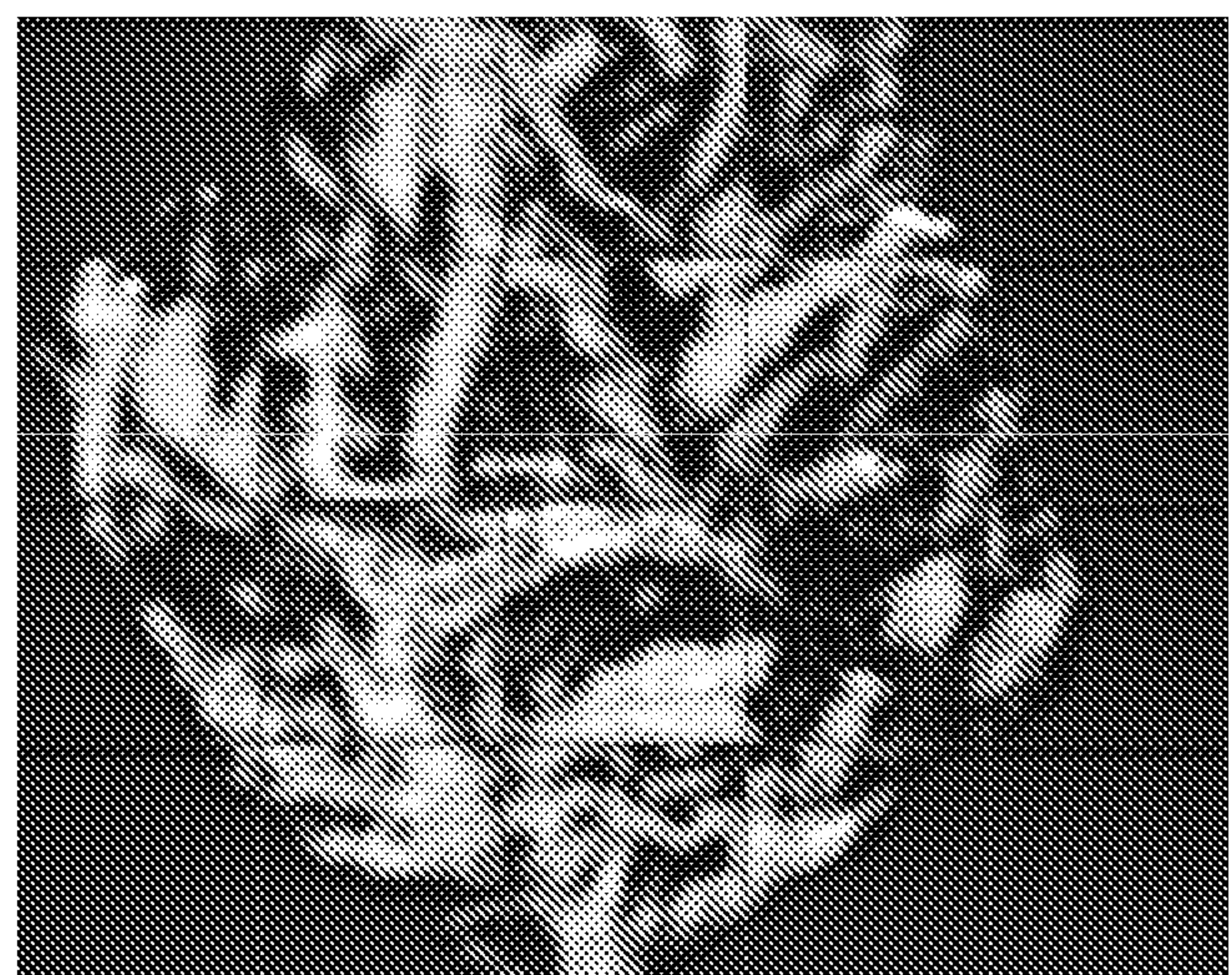


FIG. 7G

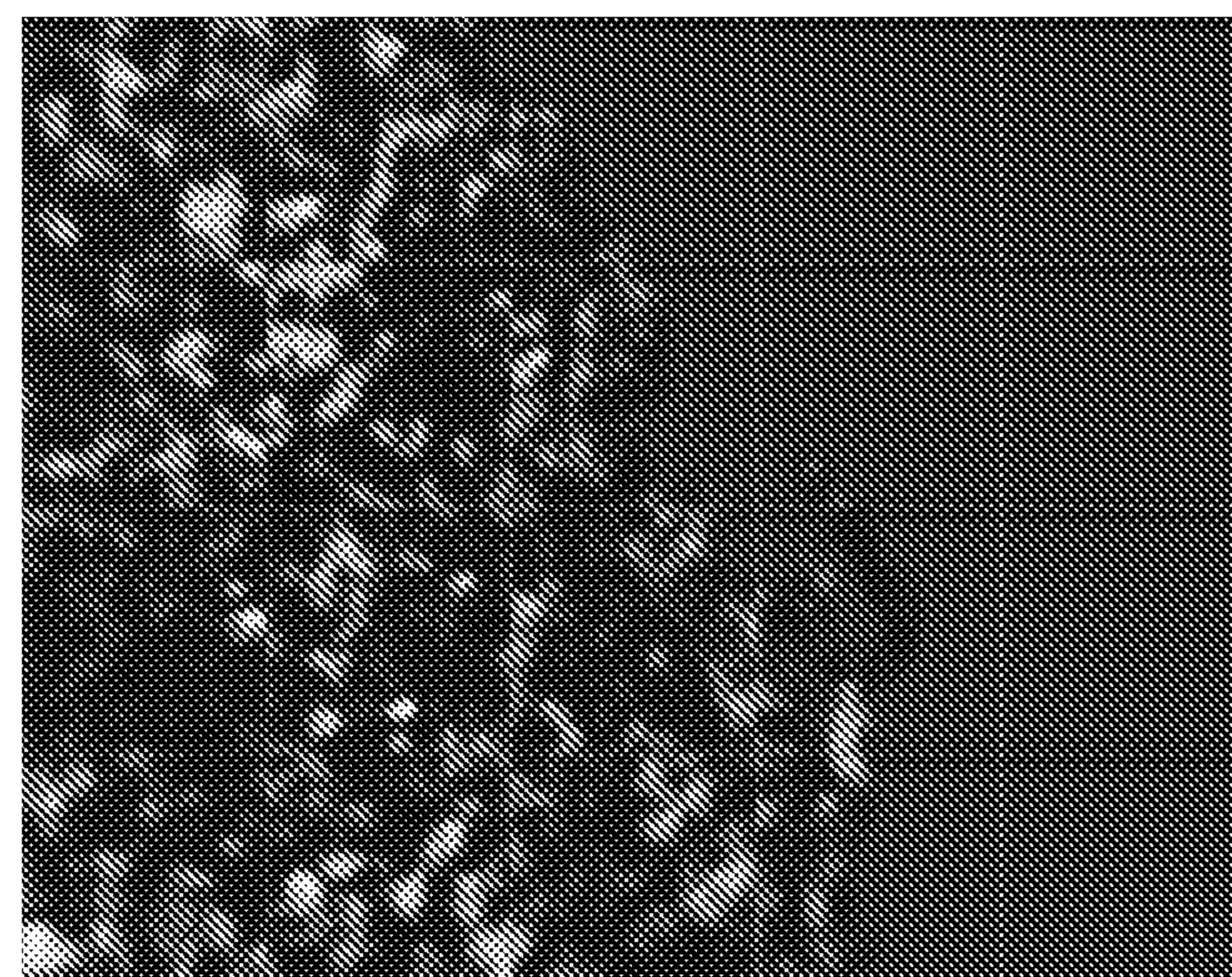
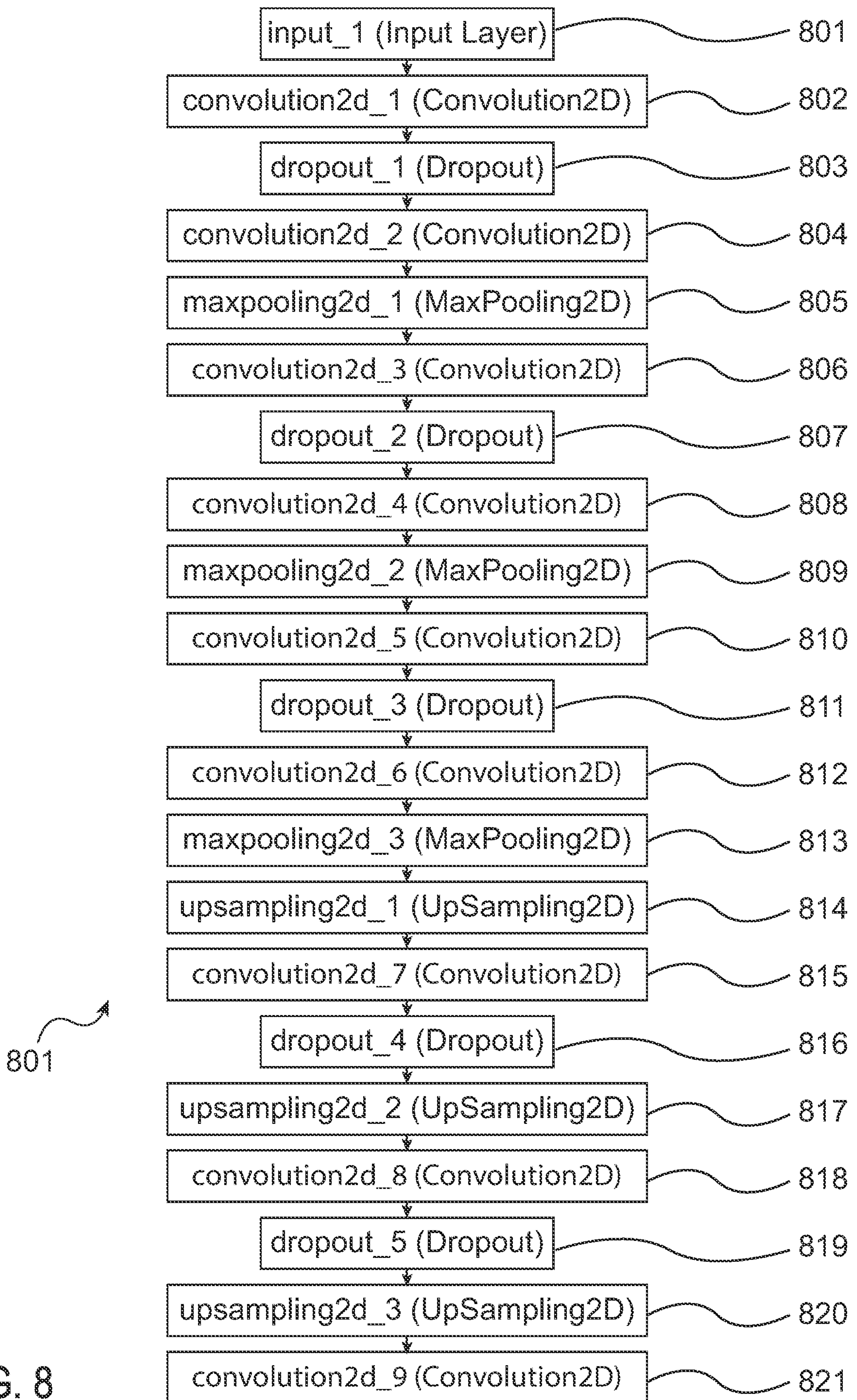


FIG. 7H

12/21



13/21

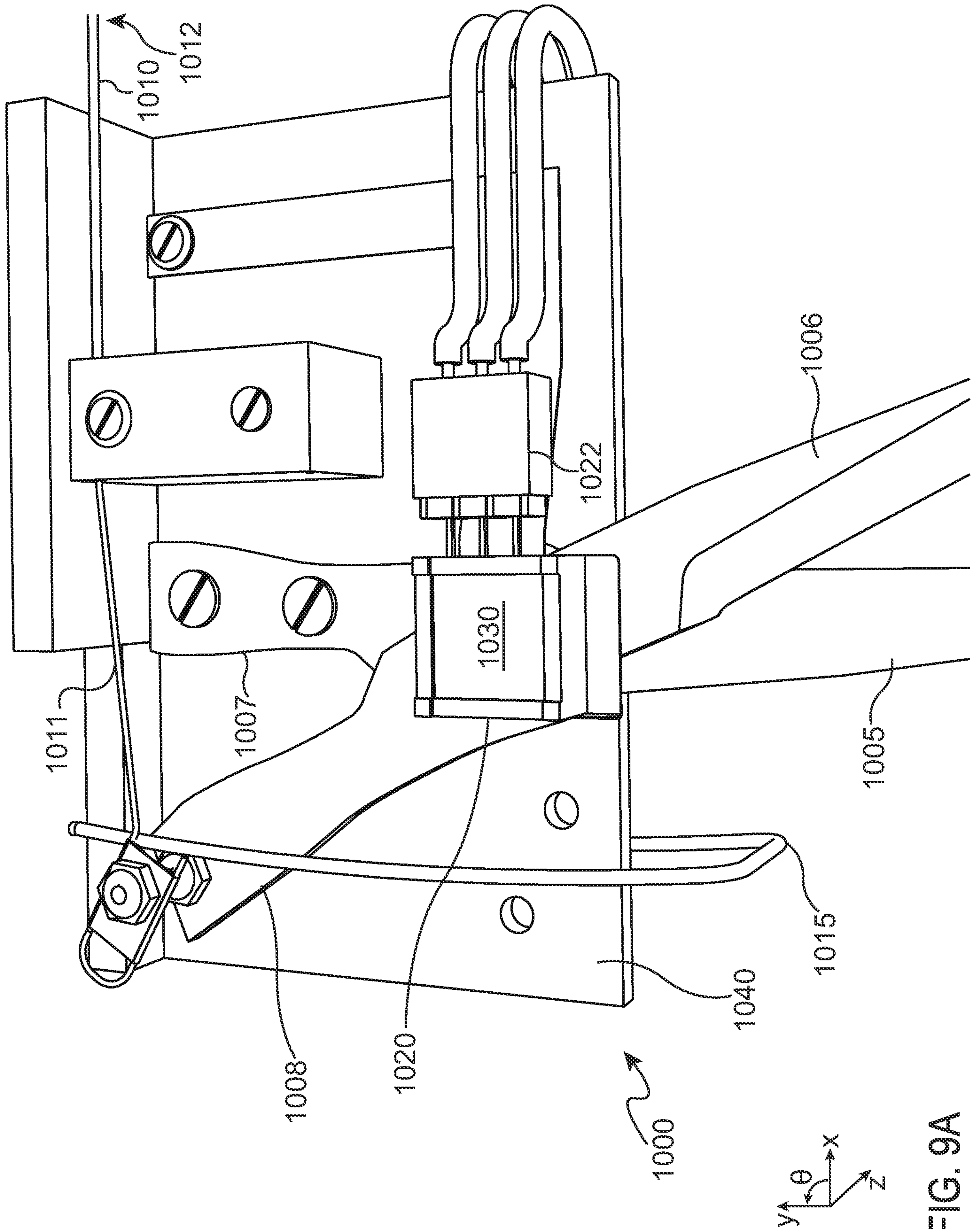


FIG. 9A

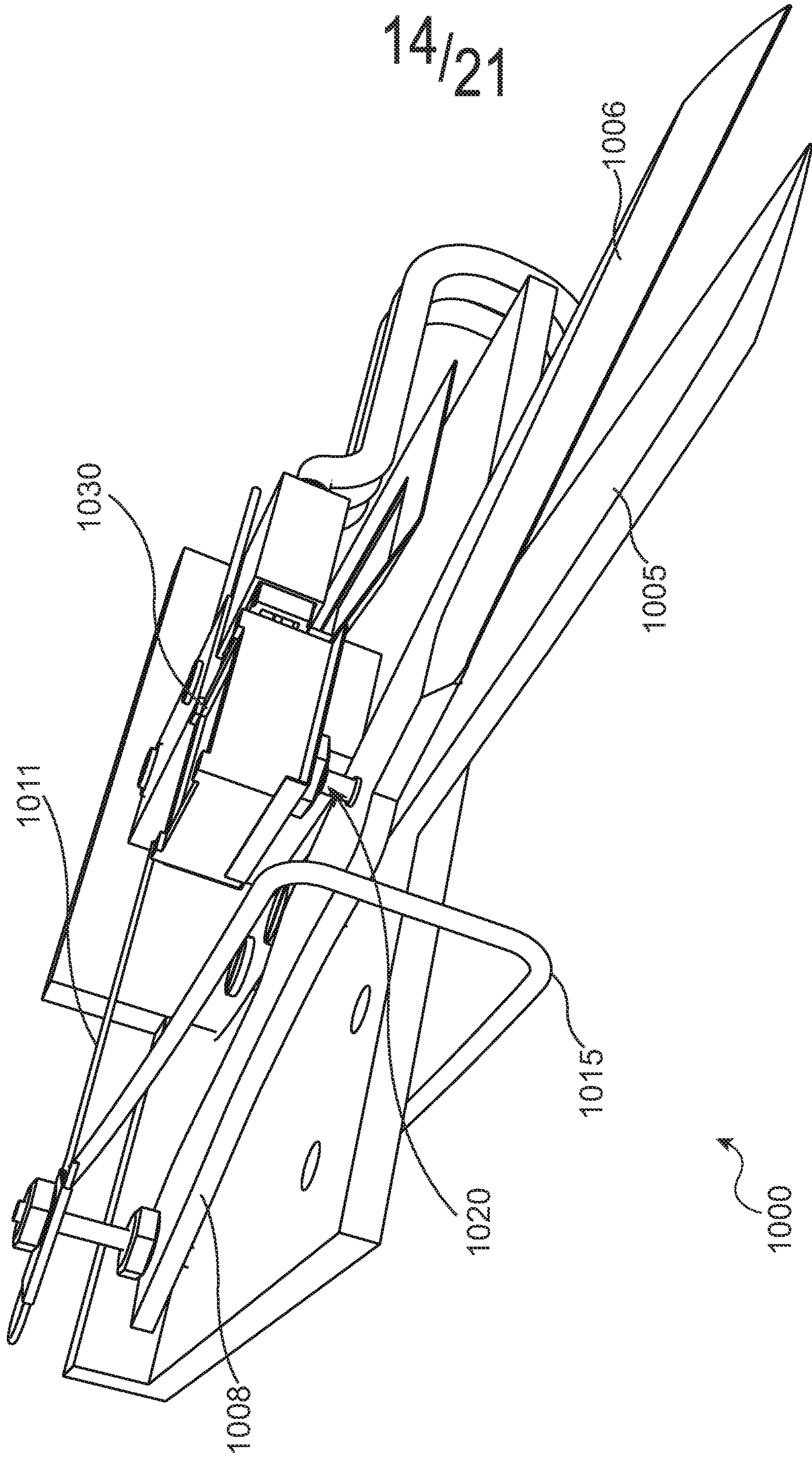


FIG. 9B

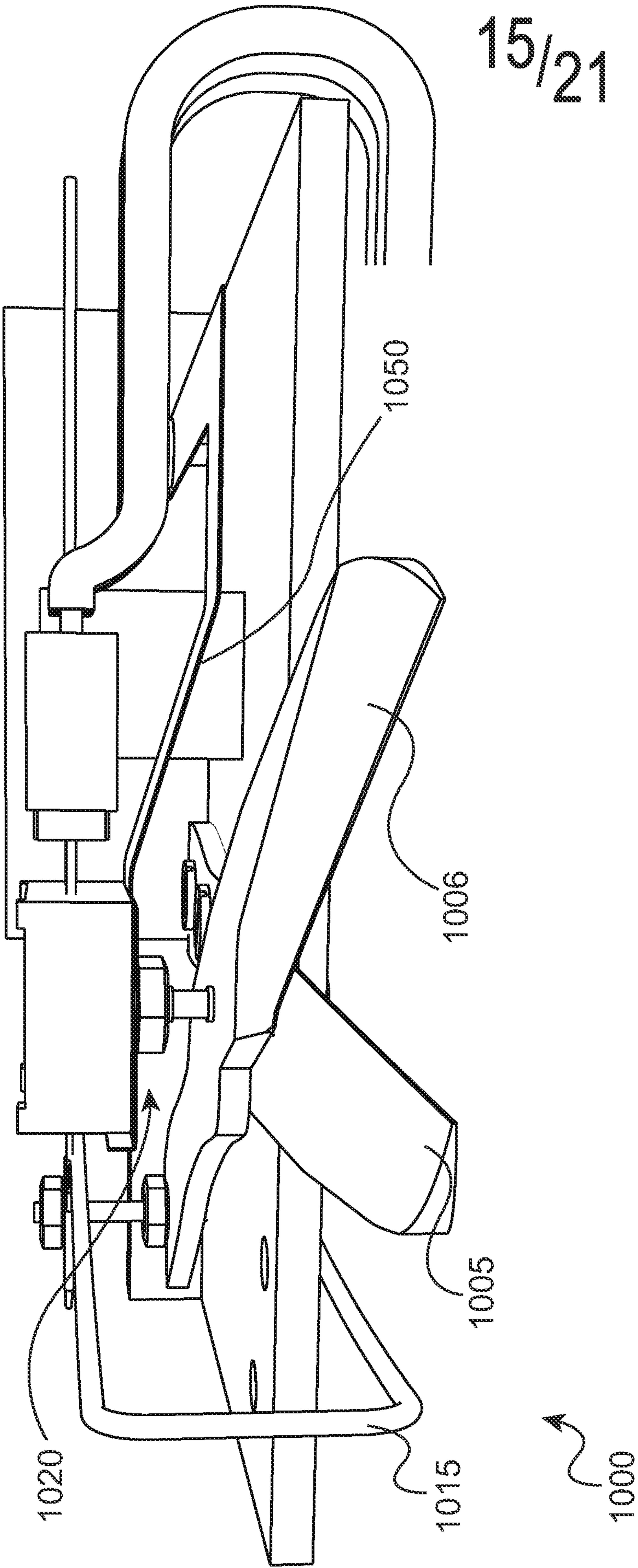


FIG. 9C

16/21

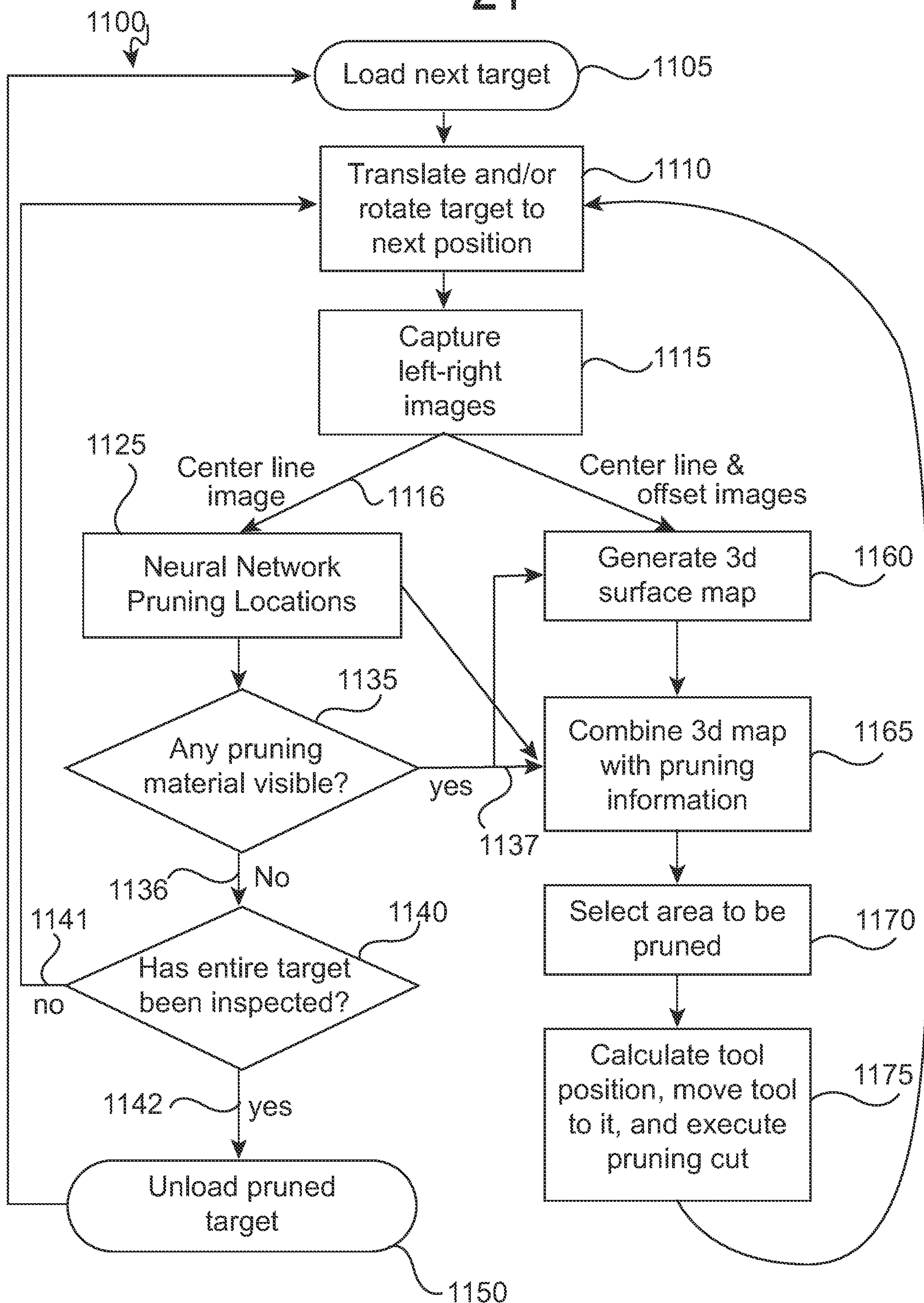


FIG. 10

17/21

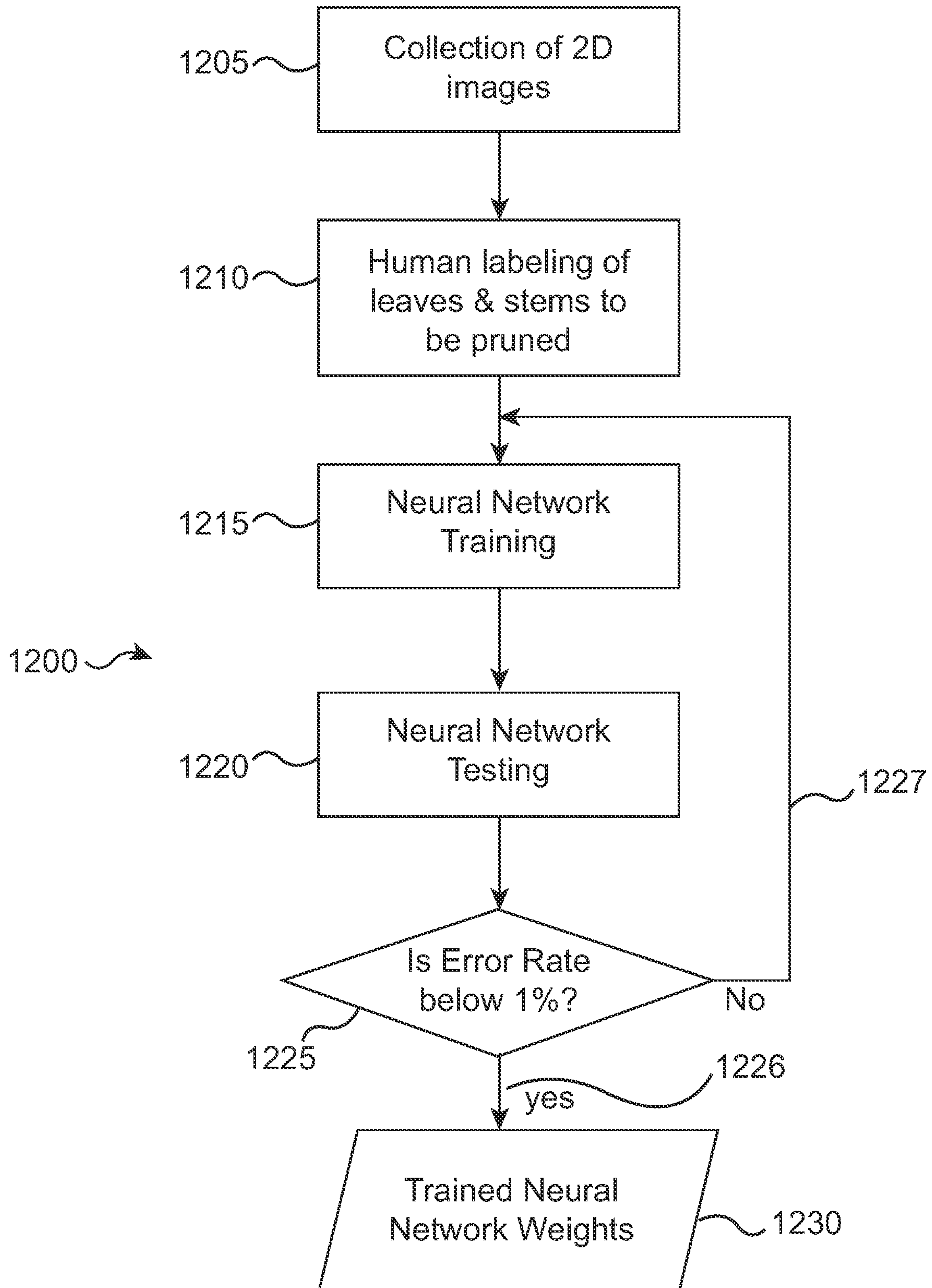
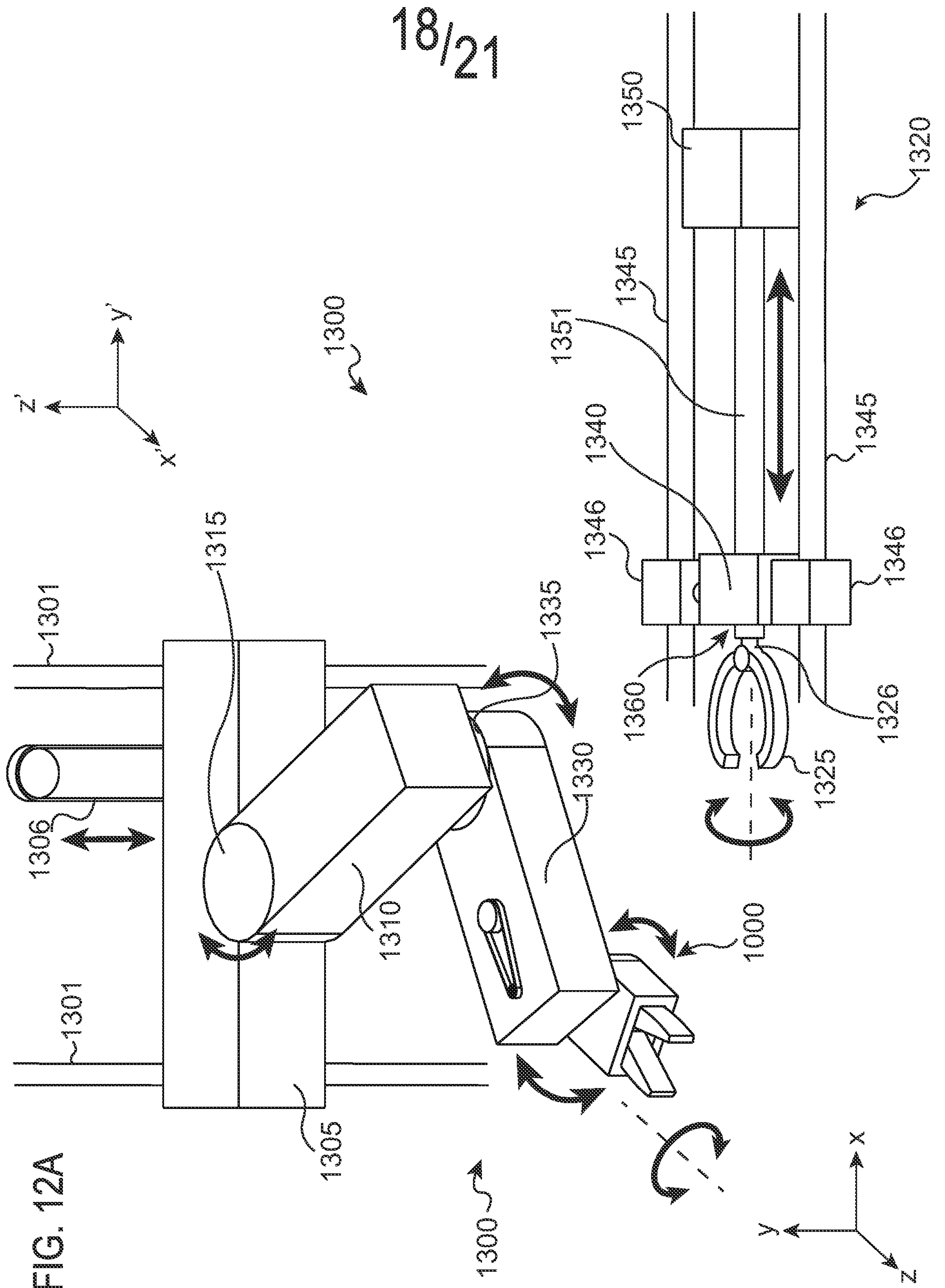


FIG. 11



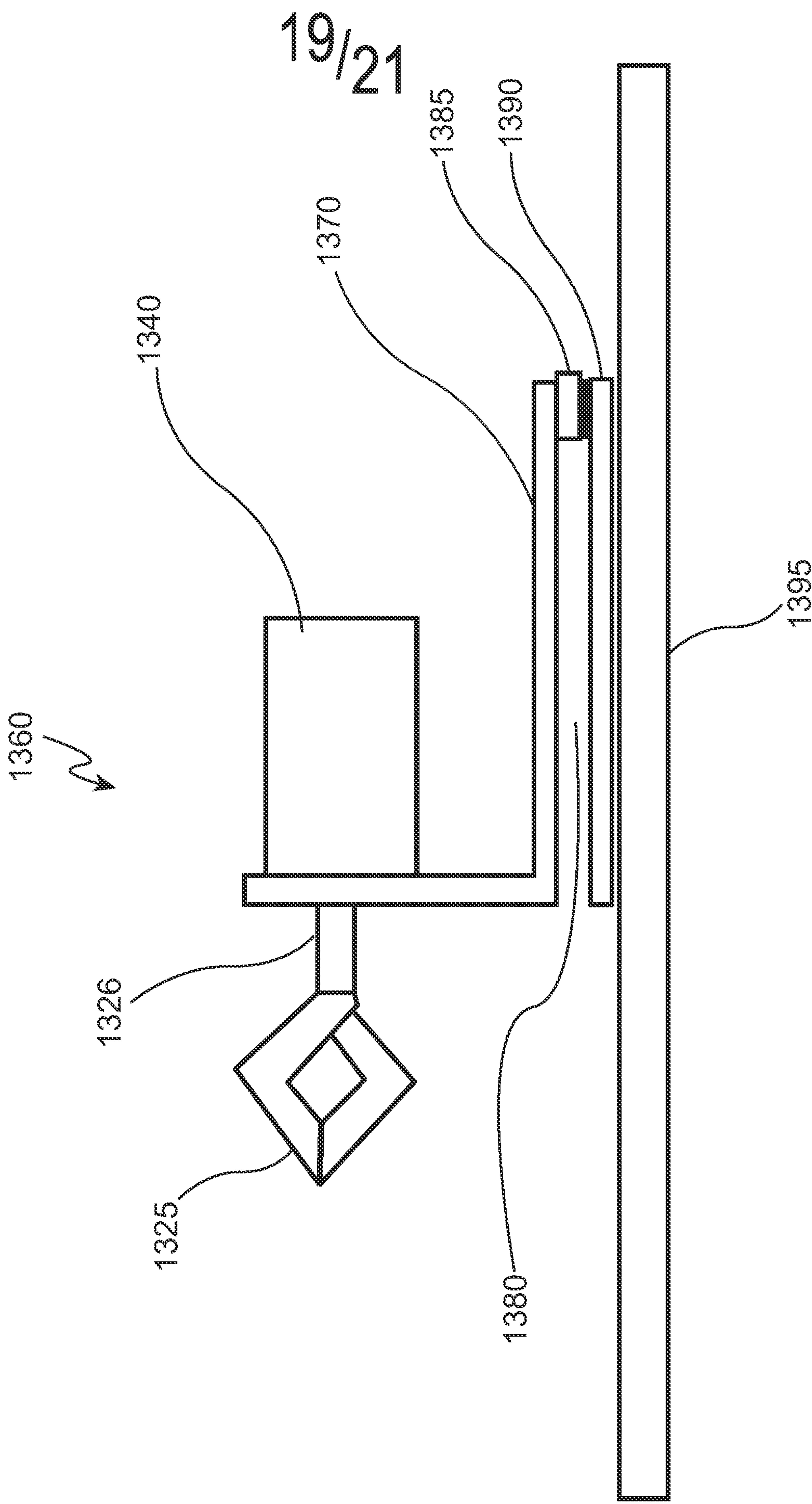


FIG. 12B

20/21

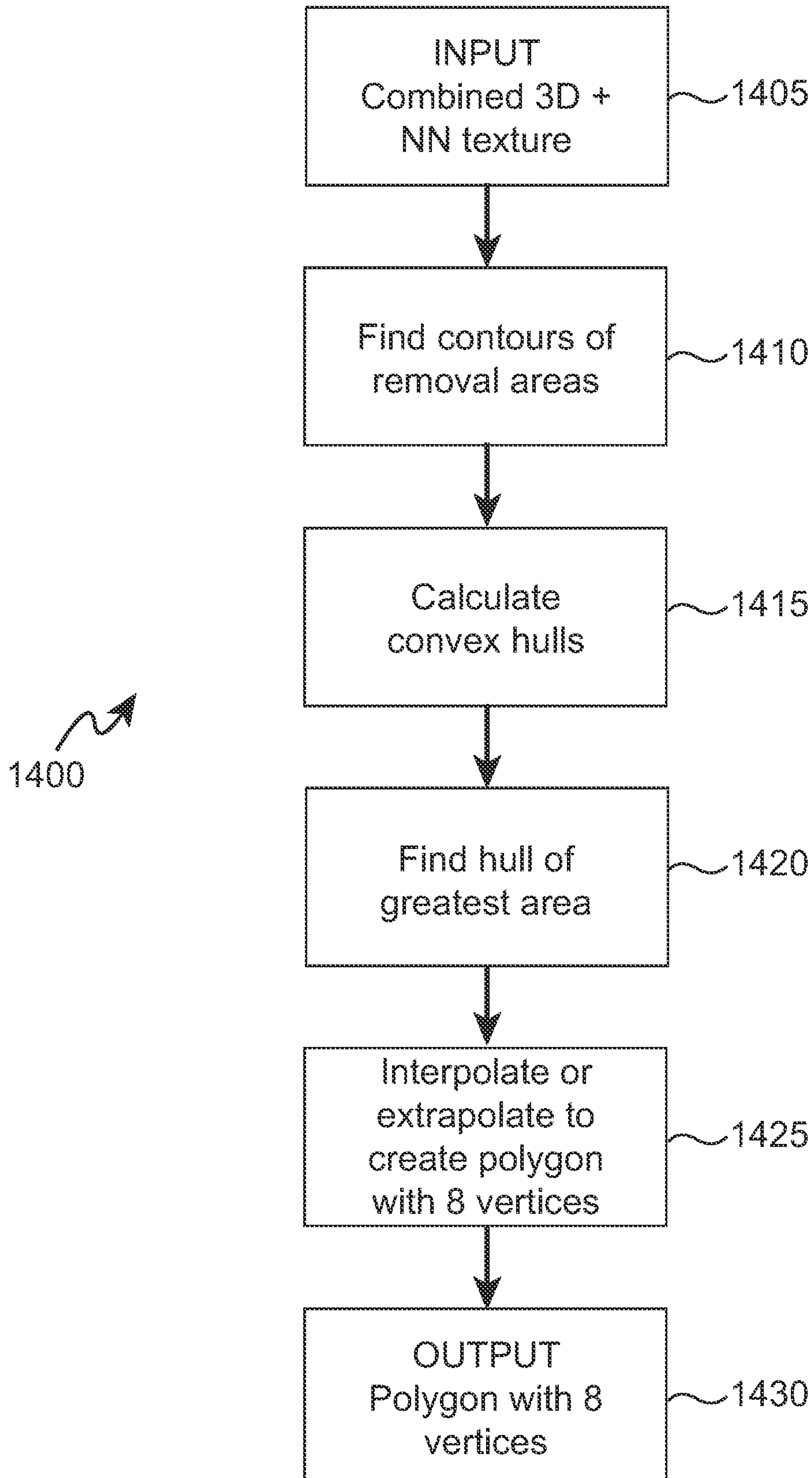


FIG. 13

21/21

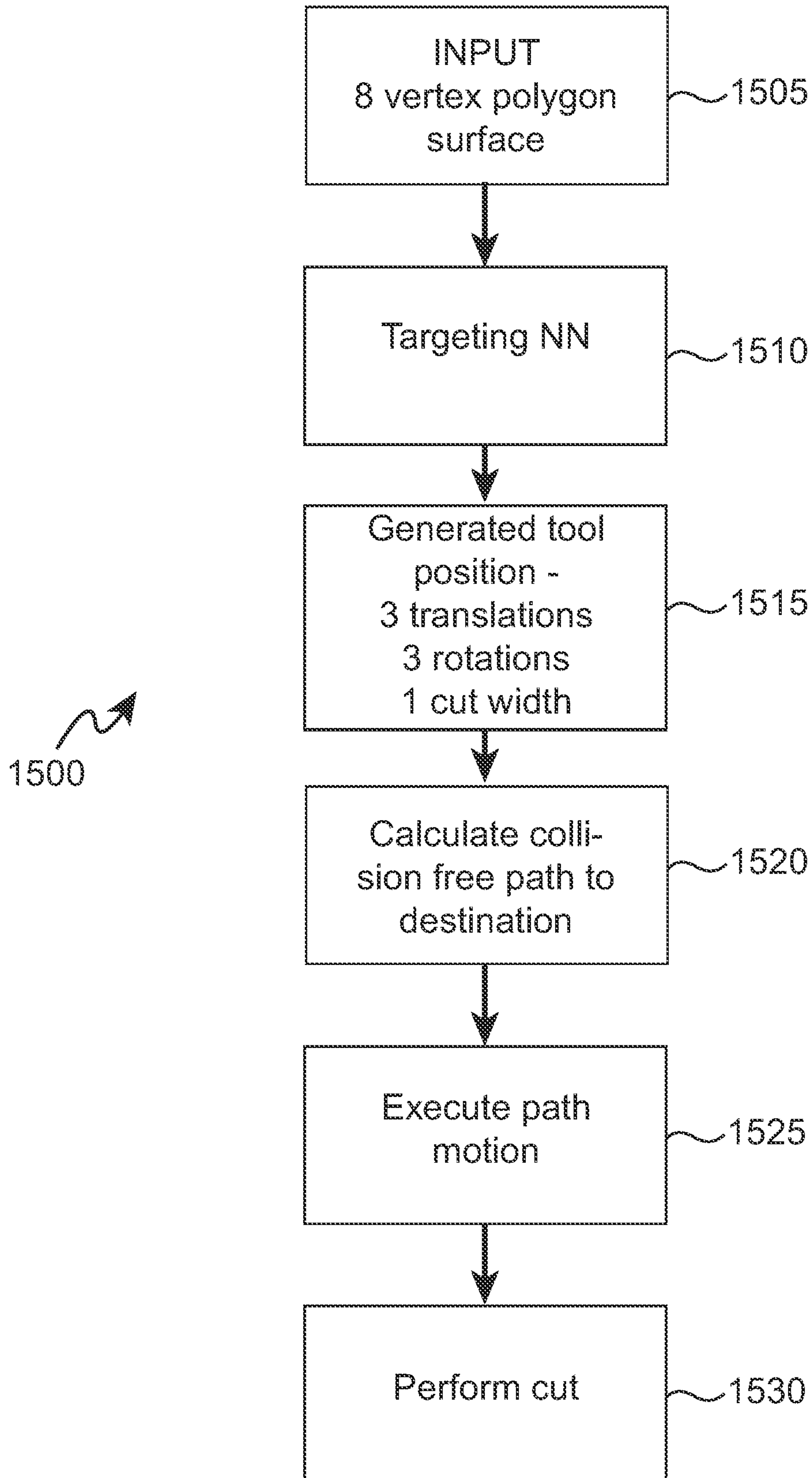


FIG. 14

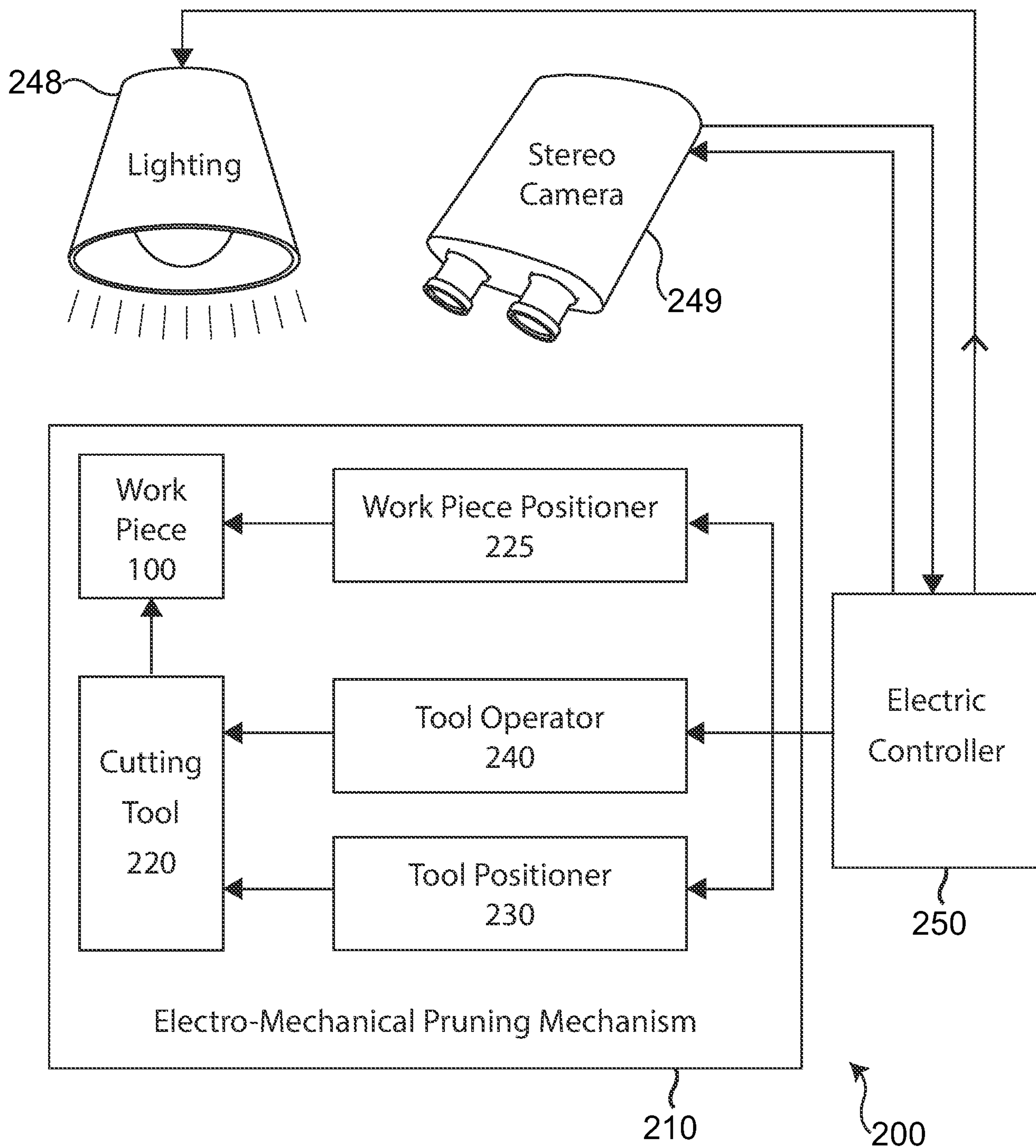


FIG. 1