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Progress in Fully Automated Abdominal CT Interpretation

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Abstract

OBJECTIVE—Automated analysis of abdominal CT has advanced markedly over just the last few years. Fully automated assessment of organs, lymph nodes, adipose tissue, muscle, bowel, spine, and tumors are some examples where tremendous progress has been made. Computer-aided detection of lesions has also improved dramatically.

CONCLUSION—This article reviews the progress and provides insights into what is in store in the near future for automated analysis for abdominal CT, ultimately leading to fully automated interpretation.

Keywords

computer-aided detection; image processing; CT; segmentation; volumetrics

Unlike for images of the brain and breast, automated analysis of images of the abdomen has been a relative latecomer to radiology. However, the pace of innovation for automated abdominal image analysis has accelerated in just the last few years. Much of this progress has focused on CT, the workhorse of abdominal diagnosis. For example, in a concerted effort over the last 15 years, great progress was made in image processing of CT colonography, leading to such advances as virtual colonoscopy flythrough and computer-aided detection (CAD) of polyps. Beginning in the same time frame and extending to the present, numerous articles describe methods to automatically detect, quantitate, and classify imaging findings on routine abdominal CT. These advances are moving the field closer to achieving the promise of fully automated image analysis and interpretation [1, 2].

Automated image analysis will be considered here in the broadest sense, including quantitative analyses and CAD and classification of disease. This review will cover the broad swath of applications in the abdomen, including organ, lymph node, adipose tissue, muscle, bowel, spine, and tumor analysis. Some speculations about the future of this dynamic field will conclude the review.

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Overview

Radiologists perform numerous high-level tasks when interpreting abdominal CT images. These tasks include assessment of organs and detection, classification, and measurement of lesions. Incidental findings must be considered and accepted or rejected. The findings must be put into the proper clinical context of the particular patient. For example, the knowledge that a patient has cancer influences the classification of a new lesion as metastatic versus infectious or inflammatory.

Each of these tasks is amenable to automation. Organs can be located by the computer using atlas- and landmark-based methods. Organ volume and shape can be assessed by finding the edges of the organs in three dimensions, a process known as segmentation. Lesions can be detected and segmented by assessing the patterns of Hounsfield unit intensities in the organs to identify anomalies. Example patterns include variations in intensities, texture, and shape. The quantitative measurements of these patterns are known as features.

To perform accurate detection and segmentation, organs and lesions must be distinguished from other surrounding tissues to avoid false recognition. To do so, features calculated for organs, lesions, and surrounding tissues are fed into classifiers to teach the computer how to distinguish them. The final outputs include those useful for diagnosis (true-positives) and incorrect ones that are not useful (false-positives). At the present time, for most applications, the computer always produces false-positives, necessitating radiologist review. However, the number of false-positives is steadily decreasing as the computer techniques improve.

There are two approaches to developing accurate automated radiologic image analysis software. In one, the software developer designs (handcrafts) features that best identify a particular disease. For example, curvature and shape are useful features for distinguishing polyps from normal colonic mucosa [3-4]. In the other, generic features are used and a machine-learning algorithm is taught to distinguish disease from nondisease sites by being trained on labeled cases, without the need for handcrafted features. The latter approach, which is made feasible by recent advances in computer science known colloquially as deep learning, is increasingly being used because it markedly increases the efficiency of image analysis development [5].

To perform fully automated abdominal CT image interpretation at the level of a trained radiologist, the computer must assess all the organs and detect all the abnormalities present in the images. Although this is a seemingly daunting task for the software developer, the numbers of organs and potential abnormalities are finite and can be addressed methodically. This methodical approach has been pursued by numerous investigators in the field and is reviewed in the next sections. Because the literature is vast, representative examples of the various approaches are described.

Organs

The automated localization and volume assessment of the abdominal solid visceral organs is a major area of investigation [6]. The liver, spleen, and kidneys have been the most studied of these organs. A number of different techniques have been used for detection. One is

identification of important anatomic landmarks, such as the diaphragm, important vessels, and spinal levels [7]. Another is the registration of images to a labeled anatomic atlas [8–9]. Advances in organ analysis have been accelerated by open challenges or competitions in which various research groups compete to obtain the most accurate organ segmentations on a common dataset [10–11].

Multiorgan Analysis

A number of investigators have studied methods to identify and measure multiple abdominal organs simultaneously on CT [12–16]. By considering the organs in this way, constraints such as relative organ positions and nonoverlap can be enforced. Accuracy has generally been best for the liver, spleen, and kidneys (> 92%) and lower for more variable organs, such as the gallbladder and pancreas (67–73%) [13]. CAD for simultaneous identification of multiple organs frequently relies on the use of one or more labeled atlases [15]. However, registration of new cases to the different cases in the atlas is usually time consuming, even with modern computer hardware. Solutions to the problems of missing organs in a multiorgan framework, such as nephrectomy or splenectomy, have also been proposed [17].

Liver and Spleen

Manual assessment of organ volumetrics is time consuming and inefficient. Radiologists tend to either over- or underestimate the presence of organomegaly when using longitudinal measurements such as craniocaudal length. Recent advances in image processing have led to fully automated software that can measure organ volumes [18–19]. The volumetric automated measurements are highly reproducible and accurate and enable more routine organ volumetrics in clinical practice. Nomograms have been developed for liver and spleen volumetry [20–21]. For example, normal liver volumes averaged 1.51 ± 0.25 L, and normal spleen volumes averaged 0.24 ± 0.08 L. For livers, it was helpful to calculate the ratio of liver volume to body surface area (i.e., the H-score). Using the H-score, mild and massive hepatomegaly were defined as exceeding 0.92 and 1.08 L/m², respectively. Mild and massive splenomegaly were defined as exceeding 0.31 and 0.43 L, respectively.

Improved liver segmentation on unenhanced CT images has been reported [22]. The segmentation of livers with unusual shapes or with large lesions has been investigated [23]. Liver segmentation can be performed very rapidly using marginal space learning, with detection times less than half a second reported [24].

The biliary tract and hepatic vasculature can be automatically extracted and analyzed [25–26]. Hepatic vessel analysis has been used for treatment planning, including surgery and radiofrequency ablation [27–29]. Liver volumetrics and vessel analysis are useful for liver transplantation [30].

Kidneys

Automated and semiautomated renal volumetrics have been reported [31–33]. Automated renal cortex segmentation and measurement have been evaluated on healthy kidney donors [34].

Pancreas

The pancreas is a highly deformable organ that has a shape and location that is greatly influenced by the presence of adjacent structures. This makes automated image analysis of the pancreas extremely challenging. A number of different approaches have been taken to automated pancreas analysis, including the use of anatomic atlases, the location of the splenic and portal veins, and state-of-the-art computer science methods such as deep learning [8, 9, 35–41] (Fig. 1).

Bladder, Uterus, Prostate, and Rectum

Bladder and bladder tumor segmentation and CAD on CT have been reported. For example, bladder cancers were automatically detected during CT urography [42]. At 4.3 false-positives per patient, the sensitivity for detecting bladder cancers was 84.9%. Bladder segmentation was done using a method that separately segments the contrast-enhanced and unenhanced regions of the bladder lumen [43, 44]. For the assessment of pT0 (complete response), the segmentation technique was found to be equivalent to manual 3D segmentation and superior to Response Evaluation Criteria in Solid Tumors (RECIST) and World Health Organization assessments [45].

Segmentation of the bladder, prostate, and rectum were reported [46]. The method was evaluated on CT scans from 188 patients. With an average computation time of under 10 seconds, the average errors were 2.4, 2.8, and 4.2 mm for prostate, bladder, and rectum, respectively.

Pelvic organ segmentations have obvious applications in radiation treatment planning [47–50]. An example is segmentation of the uterus and cervix [51].

Lymph Nodes

Lymph node analysis is of crucial importance for patients with cancer. In general, the RECIST guidelines are used to evaluate lymph nodes in such patients [52]. A number of investigators have developed automated software for detection and measurement of abdominal adenopathy [53–61] (Fig. 2). Sensitivities for abdominopelvic and retroperitoneal lymphadenopathy are 80–83% at about three false-positives per volume [56, 59].

Tumors

Liver Metastases

Liver tumor detection and segmentation have been featured in a number of works. Semiautomated liver tumor segmentation was reported elsewhere [62]. The system could segment the normal liver, enhancing tumor and necrotic tumor with Dice similarity coefficients (a measure of segmentation accuracy) of 93%, 74%, and 72%, respectively. Liver tumor detection and tumor burden—that is, the volumetric fraction of tumor within the liver—were also reported [19]. All of the tumors were detected at a false-positive rate of 2.3 per scan. The tumor burden was estimated with 0.9% error.

A liver tumor segmentation challenge occurred in 2008 [63]. The team with the highest score reported a volumetric overlap error of 31% and an average symmetric absolute surface distance of 1.6 mm [64]. Three other participants in the challenge reported the results of their semiautomated methods [65]. Two of the three evaluated methods were superior but still had high error rates; for example, there were median relative absolute volume differences of about 10% between the semiautomated segmentation and the reference manual segmentation.

Kidney Lesions

Renal lesion volumetrics have been reported [66]. Automated detection of exophytic kidney lesions on CT colonography has been shown [67]. Renal calculi may be accurately detected, with sensitivities exceeding 90% and false-positive rates below one per patient, particularly for larger calculi [68]. Kidney tumor growth rate prediction has been reported [69].

Automated tumor analysis enabled a radiomics study of hereditary kidney cancer [70]. Different hereditary kidney tumors, such as von Hippel–Lindau syndrome, Birt-Hogg-Dubé syndrome, and hereditary papillary renal carcinoma, were distinguishable to a greater or lesser degree according to lesion contrast enhancement and shape characteristics.

Pancreatic Lesions

Growth modeling of pancreatic neuroendocrine tumors has been reported in patient populations where the tumors are not excised until they reach a certain size [71–72]. Tumor growth modeling takes into account such factors as tumor blood flow and the effects of adjacent tissues and may one day permit the accurate estimation of when the tumor size will exceed the threshold for surgical intervention.

Peritoneal Ovarian Metastases

CAD of peritoneal metastases from ovarian cancer was the subject of an investigation [73]. The authors showed how perihepatic and perisplenic ovarian cancer metastases could be detected when they caused scalloping of the organ surface. The technique detected such metastases with a sensitivity of 87% at a false-positive rate of two per patient. One significance of this investigation was that it showed that detection of metastases was possible for lesions not just within organs but also those abutting organs. Detection of peritoneal masses that do not abut organs is an area in need of investigation.

Bowel

CT Colonography

Research in CT colonography image analysis underwent intense investigation between about 1996 and 2014. This activity has tapered recently as issues relating to clinical implementation have taken precedence.

A number of CAD systems were reported for colonic polyp and mass detection at CT colonography [3, 4, 74–84]. Review articles cover this topic in more detail [85–87]. Advances in CAD of the colon are leading to improved polyp and mass detection accuracy

[88–96]. Different reading paradigms for the use of CAD for polyp detection have been investigated, including the first-, concurrent-, and second-reader paradigms [97–98].

Electronic cleansing of the colon in the laxative-free or reduced-preparation setting has been proposed with promising results [99–102]. The use of dual-energy CT for electronic cleansing has been proposed [103–105].

Crowdsourcing has been applied to understand perceptual factors important for improving the interpretation of CT colonography using CAD [106–107]. For example, crowdsourcing experiments showed that video fly-arounds of polyps on the endoluminal view led to significant gains in detection performance.

A number of investigations showed how to register the supine and prone CT colonography images longitudinally or circumferentially [108–113]. Approaches to such registration have included using the teniae coli as fiducial markers and finding ways to register similar haustral folds. One registration technique was evaluated in a radiologist observer trial and for coregistration of polyps at follow-up surveillance [114–115]. Recent work has shown that the marginal artery of the colon follows the course of the tenia mesocolica and can serve as a fiducial marker for locating the colon in areas of collapse [116–117] (Fig. 3).

It has been shown how to accurately match findings at CT colonography with those of optical colonoscopy [118–120]. This has generally been done by mapping the length of the central path along the colon lumen to the polyp from CT colonography to optical colonoscopy. One such technique refines the prediction of the polyp location by estimating the straightening of the colon that occurs as the colonoscope is inserted into it [121].

Small- and Large-Bowel Segmentation

The small bowel measures approximately 22 feet in length and is tightly coiled in the abdomen. It has been considered to be a relatively intractable organ for automated image analysis until recently. It is now known that the mesenteric vasculature can be used to accurately locate the small bowel on ultra-high-resolution CT angiography images [122–123]. This method has potential applications for CAD of small-bowel tumors, obstruction, and inflammatory bowel disease.

The colon can be distinguished from the small bowel by automated software [124] (Fig. 4). The method relies on detecting the colonic mesenteric vasculature and using a colon location likelihood map taken from CT colonography studies. The technique enabled rejection of most colon false-positives by use of a small-bowel detector. A preliminary investigation has been reported on automated detection of small-bowel strictures on CT enterography [125].

Typhlitis or Colitis

Colonic inflammation can be detected by automated software on noncolonographic images by searching for thickened bowel wall. Preliminary investigation shows the feasibility of typhlitis and colitis detection on CT of immunocompromised patients [126]. Using deep learning, 85% of colitis regions were properly detected at a false-positive rate of one per image [127].

Bone

There has been rapid recent progress in automated analysis of bone on CT. Close at hand is complete spine CT image analysis. Much of the research has been conducted on larger-FOV body images in addition to smaller-FOV spine images. Examples include fully automated vertebral level labeling, bone mineral densitometry (i.e., quantitative CT), detection and grading of compression and traumatic vertebral fractures, and detection of metastases, degenerative disease, and epidural masses.

Vertebral Level Labeling

Vertebral level labeling or partitioning is useful for anatomic and lesion localization. It is also required for most other automated spine analysis tools. Automated spinal extraction and partitioning on large-FOV body CT scans have been reported [128–130].

Bone Mineral Densitometry (Quantitative CT)

Quantitative CT is typically done with the use of a densitometry phantom positioned beneath the patient. Quantitative CT can also be performed without a phantom with appropriate calibration of the scanner [131]. Recent work has shown good accuracy and agreement comparing quantitative CT with dual-energy x-ray absorptiometry [132]. This research has opened the possibility of fully automated bone densitometry assessments that are efficient and rapid for all body CT scans, including screening studies such as CT colonography.

Compression Fractures

Vertebral compression fractures are a significant cause of morbidity, particularly in older patients with osteoporosis. Despite their importance, vertebral compression fractures are often overlooked on body CT [133]. Automated software is under development that can accurately detect vertebral compression fractures [134–137]. Future versions of the software will need to both detect and grade the fractures, such as by using a visual semiquantitative scale [138].

Traumatic Fractures

It is crucial to detect vertebral fractures in patients with trauma. Overlooked fractures can lead to significant morbidity. Fractures can occur in the vertebral body and posterior elements. Some current CAD systems treat these two components separately.

Traumatic vertebral body fracture detection software has been reported recently [139]. The software digitally strips the vertebral body cortex and looks for fractures in the cortical shell. The software had a sensitivity of 92% and false-positive rate of 1.6 per patient in 67 test set patients with traumatic vertebral body fractures. The fractures were also classified according to Denis column involvement [140]. Further work is under way to detect posterior element fractures [141]. On a testing dataset, the software achieved an AUC of 0.857 and 81% sensitivity with 10 false-positives per patient. Although this software might be primarily used on dedicated spine CT with a small FOV, it could also be applied to body CT scans with a larger FOV.

Degenerative Changes

Although degenerative changes in the spine are ubiquitous in older patients, in a patient with cancer, it can be challenging to distinguish subtle changes in metastases from extensive degenerative lesions on PET/CT. The cortical shell stripping described already for vertebral body fracture detection can also be applied for degenerative disease detection on body CT [142, 143]. Degenerative disease detection can be particularly valuable for assisting interpretation of sodium fluoride PET/CT in older patients with cancer with osseous metastases [144].

Metastases

Bone metastases are a frequent cause of morbidity in patients with cancer. In the setting of breast and prostate cancer, vertebral lesions may be the first sign of metastatic disease, preceding lymph node and organ involvement. Automated detection of both lytic and sclerotic vertebral metastases on body CT have been reported [145–147]. Sensitivities and false-positive rates for lytic and sclerotic metastases were 94% and 79% and 4.5 and 10.9 false-positives per patient, respectively [145, 146]. Recent improvements led to better performance, with sensitivity and false-positive rates for sclerotic lesions of 70% and three false-positives per patient [59]. Potential future applications include assessment of lesion change and early lesion detection.

Epidural Masses

Epidural masses in patients with cancer are frequently overlooked by radiologists interpreting body CT (Kim LM, et al., presented at the Radiological Society of North America 2015 annual meeting). The authors found that, in 129 patients with epidural masses proven by spine MRI, radiologists did not report the presence of epidural masses in 25% of the 244 CT studies. To address this issue, automated software has been developed that can detect epidural masses with a sensitivity of 82% and false-positive rate of three per patient [148, 149] (Fig. 5).

Adipose Tissue

Visceral fat analysis is routinely used for a number of investigations. The analysis software typically identifies the boundary between the subcutaneous and visceral fat compartments, enabling accurate measurement of both and permitting visceral fat measurement not just at the umbilicus or L4–L5 level used in manual analyses but also whole abdomen visceral fat analysis [150–152]. Approaches have also been developed to choose an optimized level for single slice analysis of adiposity [153].

Visceral fat is known to be associated with metabolic syndrome and colonic polyps [150, 154]. Visceral fat can be assessed on routine abdominal CT and on CT colonography [155–157]. An intriguing association between pericolonic fat and colonic polyps has been recently reported [158].

Muscle

Muscle analysis is important for diseases such as myositis and also for assessment of functional reserve in patients undergoing cancer therapy or surgery [159–163]. Muscle analysis is typically conducted at a single level in the abdomen (L3) using manual or semiautomated tracing of the musculature [164]. Automated image analysis is at a preliminary stage of development but shows promise in enabling whole-body muscle volumetrics [165] (Fig. 6).

Blood Vessels: Abdominal Atherosclerosis and Vessel Mapping

Automated detection of aortoiliac atherosclerosis may enable whole-body calcium scoring and epidemiologic analyses [166]. In a study of 40 CT scans with 249 atherosclerotic calcifications, a sensitivity of detecting calcifications of 83.9% was found, with one false-positive per scan. Patients were accurately grouped into one of four broad categories of aortoiliac plaque burden in 75% of cases and were off by only one category in another 20%.

Automated mapping of abdominal vessels has been proposed [26, 167, 168] (Fig. 7). The labeling provided by the mapping may be useful for surgical navigation [169]. Semiautomated volumetry of abdominal aortic aneurysms on CT has also been reported [170].

The Future

Advances are likely in several areas pertaining to automated abdominal CT image interpretation. These areas include machine learning, big data, automated report generation, multimodality image analysis, publicly available datasets and competitive challenges, investigation of other organs and diseases, and new applications. If automated interpretation is widely realized, there will be effects on radiologists that will need to be considered.

Machine Learning

Machine learning, a computer science discipline, has had a tremendous effect on the advancements in radiology CAD [86]. A recent advance in computer science is the refinement of neural networks, a type of machine learning classifier used to make decisions from data. This refinement, known generically as deep learning but more specifically as convolutional neural networks, has shown dramatic improvements in automated intelligence applications. Initially drawing attention for impressive improvements in speech recognition and natural image interpretation, deep learning is now being applied to medical images, as described already in the sections on the pancreas and colitis. The results have been particularly promising for reduction of false-positives.

Deep learning led to dramatic improvements in the performance of three different body CT CAD systems [59]. The authors improved existing CAD systems for sclerotic spine metastases, lymphadenopathy, and colonic polyps [75, 146, 171, 172]. Sensitivities improved from 57% to 70%, from 43% to 77%, and from 58% to 75%, respectively, with three false-positives per patient.

There has been a recent explosion of research activity on the use of deep learning for radiologic image analysis that is likely to continue for at least the next few years. Examples for abdominal CT analysis include pancreas and kidney imaging [36-173].

Big Data and Automated Radiology Reporting

CT scans can be analyzed in combination with their accompanying reports to enable automated report generation and efficient linking of report findings with image findings. In a study of 216,000 radiology key images identified during routine clinical interpretation of scans from 62,000 unique patients, including many from abdominal CT scans, the rate of predicted disease-related words matching the actual words in the report sentences was 56% [174]. Automated hyperlinking of report sentences mentioning specific organs to the proper CT images, along with choice of window width and level settings appropriate to the organ, has been shown [175].

Multimodality Image Analysis

CT images of a lesion can be combined with other modalities such as PET and MRI to improve segmentation. For example, assessment of lesions in the liver and pelvis was improved using cosegmentation from multimodality PET/CT and PET/MRI [176]. This topic demands further exploration.

Publicly Available Datasets and Competitive Challenges

Greater availability of CT datasets is needed to advance the field. Abdominal CT datasets are slowly becoming available, through such sites as The Cancer Imaging Archive [177] and the Visceral project [178]. For example, a dataset of 595 annotated abdominal lymph nodes in CT scans of 86 patients is available online [179]. Some datasets are released as part of various challenges and workshops, such as the Medical Image Computing and Computer-Assisted Intervention Society's Beyond the Cranial Vault workshop [180]. However, much larger datasets may be necessary to enable the computer to perform as accurately as a trained radiologist [181]. A number of companies have recently sought to collect huge proprietary radiology datasets for this purpose, including IBM, Zebra Medical Vision, and Enlitic.

Investigation of Other Organs and Diseases

Despite the tremendous progress described already, there are still some understudied organs and diseases. The gallbladder, adrenal glands, and ovaries are difficult to analyze because of their small size. Uterine anomalies and fibroids have not been the subject of fully automated image analysis. Automated quantification of ascites and the detection of pneumoperitoneum would be useful applications. Automated detection of vascular thrombosis, either bland or malignant, and collateral vessels would have clinical value. Hydronephrosis detection and grading would be useful for scan triage for immediate reading and for standardization of severity assessment.

New Applications to Improve Patient Care

An area of tremendous potential is the use of fully automated image interpretation in underserved populations to meet global health needs. Billions of patients live in countries

with limited access to trained radiologists [182]. Transport of images via teleradiology from underserved communities to trained radiologists may be insufficient to meet these patients' needs if the pace of imaging utilization accelerates. Automated analyses may be a more sustainable solution.

Another underutilized approach is the use of automated image analysis running in the background to triage patients with potentially life-threatening conditions, to reduce common interpretative errors, to perform large-scale epidemiologic studies, and to coordinate and interpret large volumes of clinical, genomic, and imaging data. As radiology practices consolidate into larger hospital-led groups, it will be more feasible to implement such systems. Such big data analyses could uncover previously unrecognized associations among imaging findings, drug treatments, and other data in the clinical record. These applications promise improvements in patient care.

Effect on the Radiologist

Autopilots for airplanes changed the role of the pilot. Self-driving cars will change the role of the driver. In both cases, the human is still ultimately responsible for the safety of the passengers. Similarly, fully automated abdominal CT image interpretation is likely to change the role of radiologists, but they will still be responsible for taking care of the patient and making the final diagnosis. The automated report could improve reading efficiency, but radiologists will need to be vigilant to avoid placing too much trust in the computer. Further research on human factors, such as visual perception, and on quality assurance and promotion of a safety culture will be required to understand potential failures of the technology when used in the clinical setting [183–185].

The use of automated image interpretation by nonradiologists will need to be considered. Such users might include radiology technologists, radiologist assistants, and nonradiologist clinicians. The technology could lead to further commoditization of radiology services.

In conclusion, advances in abdominal CT automated image interpretation are occurring at a rapid pace. In the not too distant future, these advances may enable fully automated image interpretation. Similar advances may occur in other body regions and with other imaging modalities. Risks and benefits are difficult to foresee but may include increased pressures for commoditization, better reading efficiency, fewer interpretive errors, and a more quantitative radiology report. The primary focus must ultimately be on improved patient care.

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Fig. 1.

71-year-old man with prostate cancer. Images show examples of automated pancreas detection and segmentation. Reprinted from [36]. Figure is in public domain.

A, Reference standard pancreas segmentation was performed with manual tracing (*red*).

B, Pancreas probability map was computed using deep learning. Pancreas is outlined in red.

C, Final pancreas segmentation from automated software (*green*) is superimposed on reference standard (*red*) for comparison.

Fig. 2.

65-year-old man with metastatic prostate cancer. Images show examples of automated lymphadenopathy detection. Reprinted from Hua et al. (presented at 2012 ARRS annual meeting). Figure is in public domain.

A, Original contrast-enhanced abdominal CT image shows centimetric retroperitoneal lymph node (*arrow*).

B and **C**, After lymph node detection stage (**B**) and segmentation stage (**C**), lymph node (*purple*), aorta (*green*), spine (*pink*), spinal canal (*blue*), and retroperitoneal lymph node search region (*yellow*) are shown.

Fig. 3.

51-year-old woman who underwent CT colonography. Reprinted from [117]. Figure is in public domain.

A, Supine 3D reconstruction CT colonography image shows labeled marginal blood vessel (*red*), detected teniae coli, and segmented colon. Blue indicates tenia mesocolica, yellow indicates tenia omentalis, and green indicates tenia libera.

B, Labeled marginal blood vessel, teniae, and colon are shown together. Image is example of CT colonography image with collapsed segment in sigmoid colon. Marginal blood vessel bridges region of collapse and helps determine colon connectivity there.

Fig. 4. 51-year-old man with history of midgut carcinoid tumors. Images show example of improved small-bowel segmentation by colon detection and removal. Modified from [124]. Figure is in public domain.

A, Preliminary small-bowel segmentation. Small bowel is shown in brown, and mesenteric and aortoiliac vasculature are shown in red. Arrows indicate false-positives on colon.

B, Improved small-bowel segmentation after colon removal using artery labeling and colon probability map methods. Rectangle indicates missing small bowel, false-negative introduced by method.

Fig. 5.
46-year-old man with metastatic melanoma detected on body CT. Reprinted from [149].
Figure is in public domain.

A, Original CT image shows epidural mass (*arrow*).

B, Computer-aided detection image shows epidural mass (*blue*).

Fig. 6.

51-year-old man with history of midgut carcinoid tumors (same patient as Fig. 4). Images are examples of automated muscle segmentation. Reprinted from [165]. Figure is in public domain.

A, Original CT image shows through mid abdomen.

B and **C**, On reference standard (**B**) and automated segmentation result (**C**) images, muscle is indicated in cyan.

Fig. 7.

51-year-old man with history of midgut carcinoid tumors (same patient as Fig. 4). Reprinted from [167]. Figure is in public domain.

A, Three-dimensional mesenteric vasculature segmentation was derived from contrast-enhanced abdominal CT angiography.

B, Automated anatomic labeling result is shown. AO = abdominal aorta, CA = celiac axis, SMA = superior mesenteric artery, RRA = right renal artery, LRA = left renal artery, IMA = inferior mesenteric artery, RCIA = right common iliac artery, LCIA = left common iliac artery.