



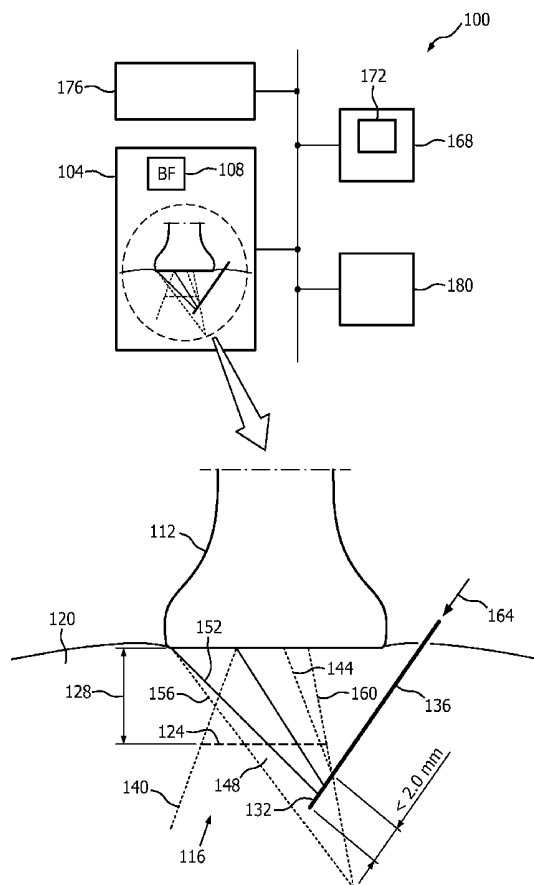
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(19) **United States**(12) **Patent Application Publication**
Parthasarathy et al.(10) **Pub. No.: US 2016/0317118 A1**(43) **Pub. Date: Nov. 3, 2016**(54) **AUTOMATIC ULTRASOUND BEAM
STEERING AND NEEDLE ARTIFACT
SUPPRESSION****G06K 9/62** (2006.01)**A61B 8/00** (2006.01)**G06T 7/00** (2006.01)(71) Applicant: **KONINKLIJKE PHILIPS N.V.**,
Eindhoven (NL)(52) **U.S. Cl.**CPC **A61B 8/0841** (2013.01); **A61B 8/461**(2013.01); **A61B 8/5215** (2013.01); **A61B****8/5269** (2013.01); **G06T 7/0012** (2013.01);**G06T 7/004** (2013.01); **G06T 7/0081**(2013.01); **G06K 9/6267** (2013.01); **G06K****9/66** (2013.01); **G06T 2207/10132** (2013.01)(72) Inventors: **Vijay Parthasarathy**, Mt. Kisco, NY
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WI (US)(21) Appl. No.: **15/105,037**(57) **ABSTRACT**(22) PCT Filed: **Nov. 28, 2014**(86) PCT No.: **PCT/IB2014/066411**

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20, 2013, provisional application No. 62/019,087,
filed on Jun. 30, 2014.**Publication Classification**(51) **Int. Cl.****A61B 8/08** (2006.01)**G06K 9/66** (2006.01)

A classification-based medical image segmentation apparatus includes an ultrasound image acquisition device configured for acquiring, from ultrasound, an image depicting a medical instrument such as needle; and machine-learning-based-classification circuitry configured for using machine-learning-based-classification to, dynamically responsive to the acquiring, segment the instrument by operating on information (212) derived from the image. The segmenting can be accomplished via statistical boosting (220) of parameters of wavelet features. Each pixel (216) of the image is identified as “needle” or “background.” The whole process of acquiring an image, segmenting the needle, and displaying an image with a visually enhanced and artifact-free needle-only overlay may be performed automatically and without the need for user intervention.



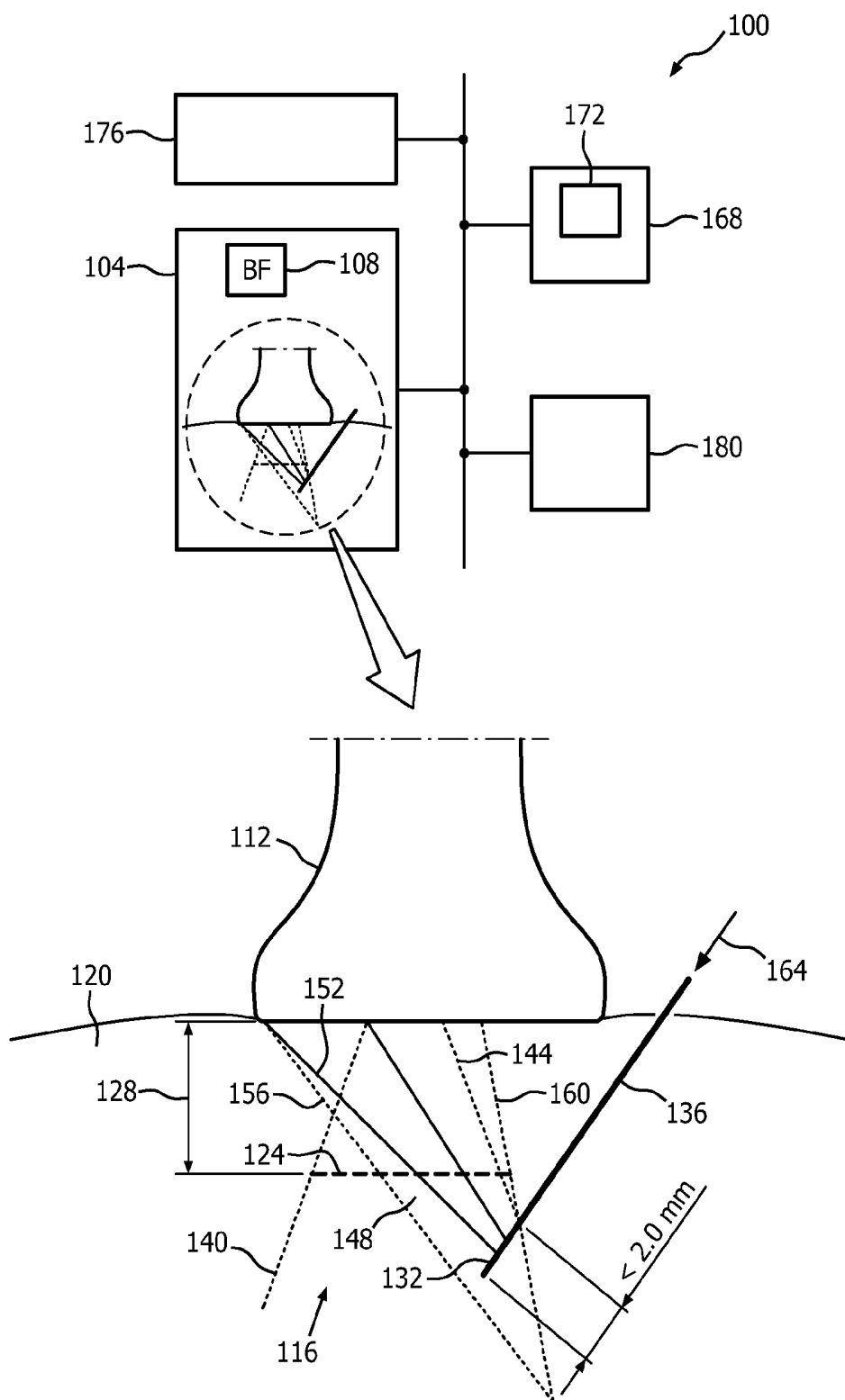


FIG. 1

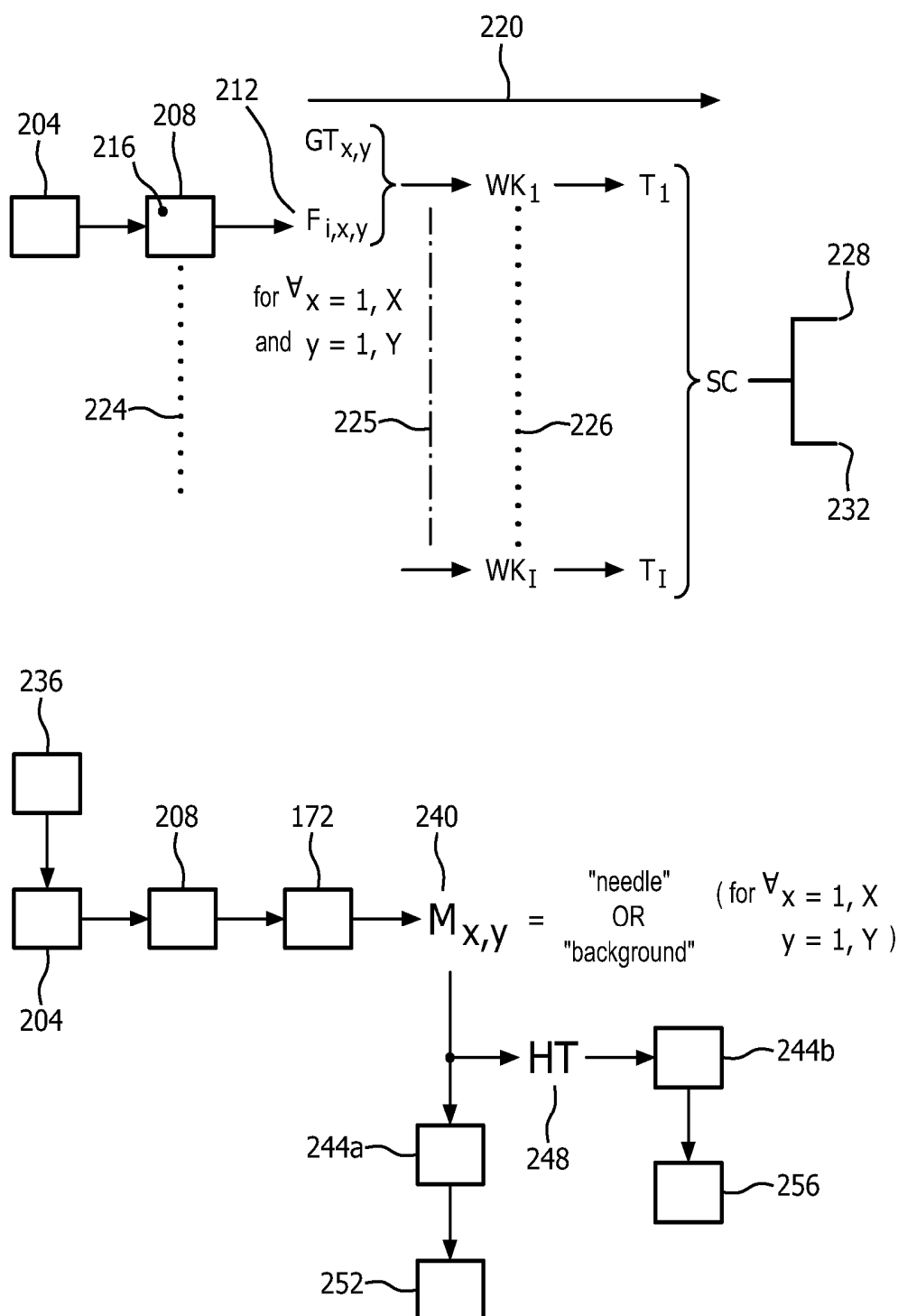


FIG. 2

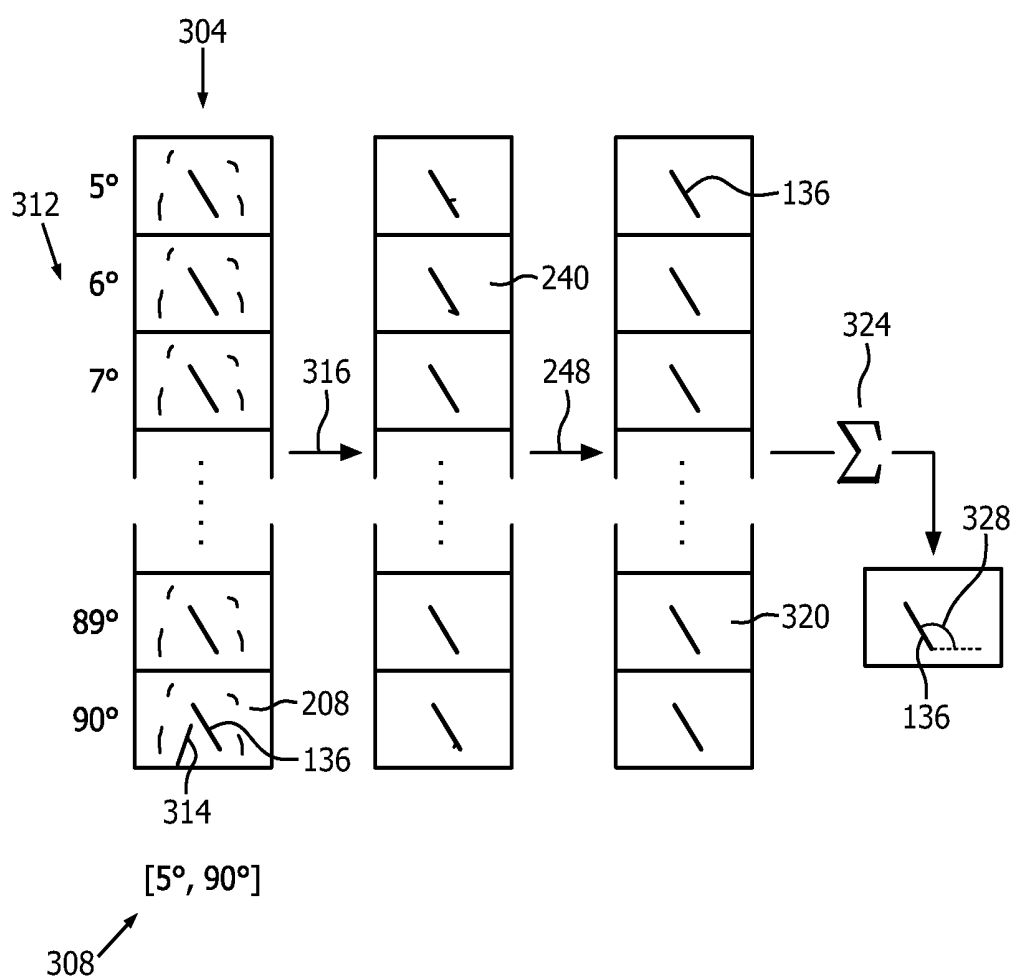


FIG. 3

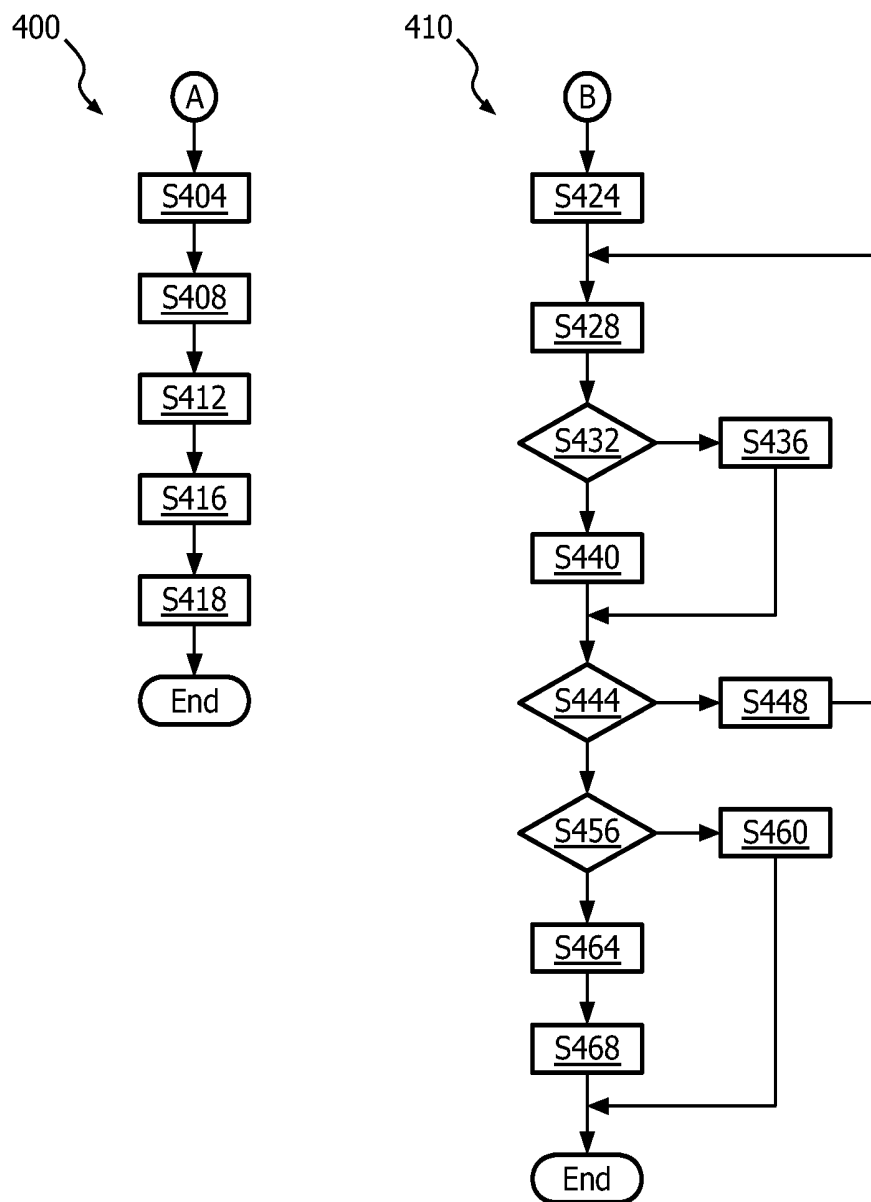


FIG. 4

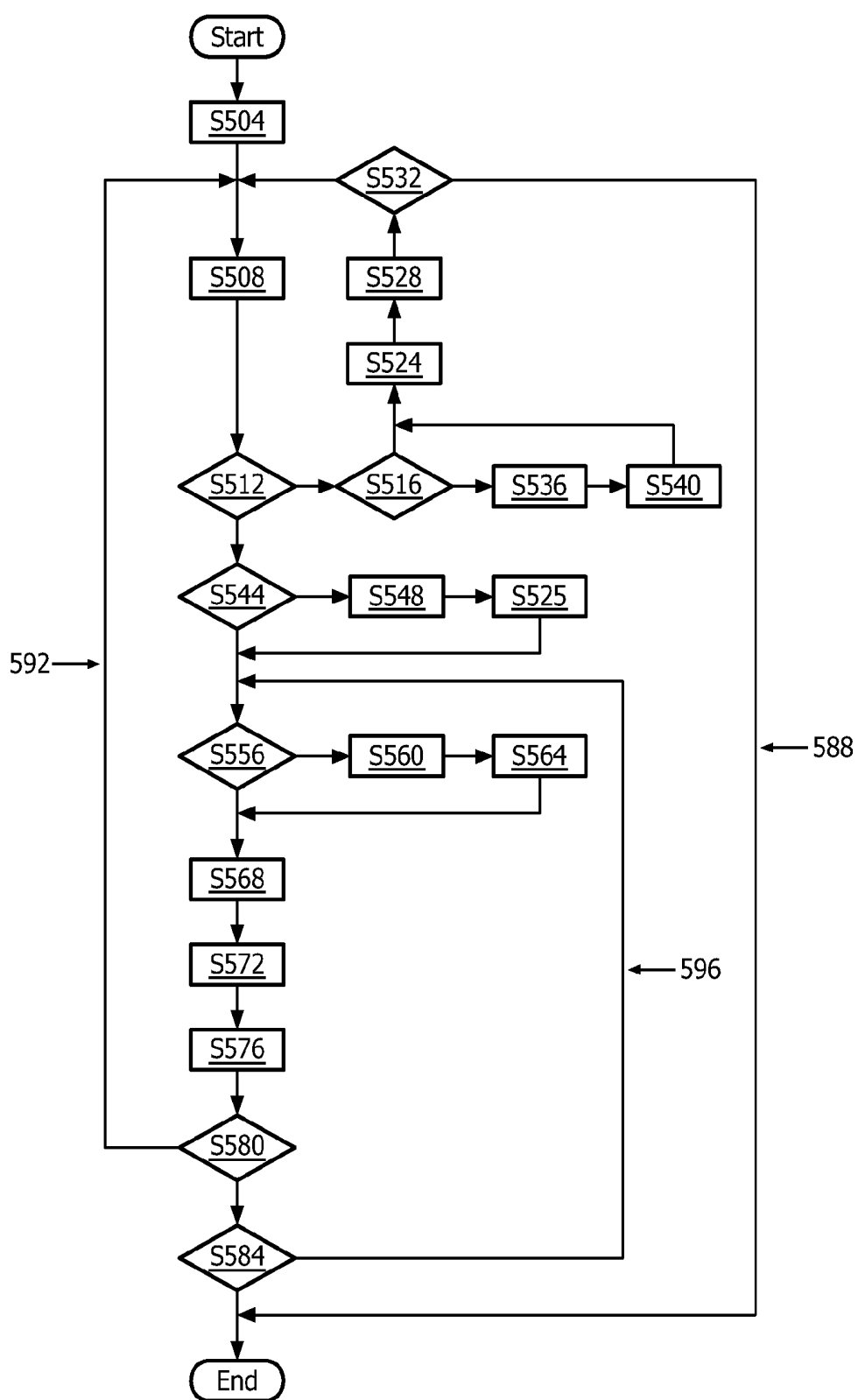


FIG. 5

AUTOMATIC ULTRASOUND BEAM STEERING AND NEEDLE ARTIFACT SUPPRESSION

CROSS REFERENCE TO PRIOR APPLICATION

[0001] This application claims the benefit of U.S. Provisional Patent Application No. 61/918,912, filed on Dec. 20, 2013 which is hereby incorporated by reference herein.

FIELD OF THE INVENTION

[0002] The present invention relates to segmenting a medical instrument in an ultrasound image and, more particularly, to dynamically performing the segmentation responsive to acquiring the image. Performing “dynamically” or in “real time” is interpreted in this patent application as completing the data processing task without intentional delay, given the processing limitations of the system and the time required to accurately measure the data needed for completing the task.

BACKGROUND OF THE INVENTION

[0003] Ultrasound (US) image guidance increases the safety and efficiency of needle guided procedures by enabling real-time visualization of needle position within the anatomical context. The ability to use ultrasound methods like electronic beam steering to enhance the visibility of the needle in ultrasound-guided procedures has become a significant competitive area in the past few years.

[0004] While real-time 3D ultrasound is available, 2DUS is much more widely used for needle-based clinical procedures due to its increased availability and simplified visualization capabilities.

[0005] With 2DUS, it is possible to electronically steer the US beam in a lateral direction perpendicular to the needle orientation, producing strong specular reflections that enhance needle visualization dramatically.

[0006] Since the current orientation of the probe with respect to the needle is not typically known at the outset, the beam steering angle needed to achieve normality with the needle is also unknown.

[0007] Also, visualization is difficult when the needle is not directly aligned within the US imaging plane and/or the background tissue contains other linear specular reflectors such as bone, fascia, or tissue boundaries.

[0008] In addition, artifacts in the image come about for various reasons, e.g., grating lobes from steering a linear array at large angles and specular echoes from the above-mentioned linear and other specular reflectors offering a sharp attenuation change to ultrasound incident at, or close to, 90 degrees.

[0009] “Enhancement of Needle Visibility in Ultrasound-Guided Percutaneous Procedures” by Cheung et al. (hereinafter “Cheung”) discloses automatic segmenting of the needle in an ultrasound image and determining the optimum beam steering angle.

[0010] Problematically, specular structures that resemble a needle interfere with needle detection. Speckle noise and imaging artifacts can also hamper the detection.

[0011] The solution in Cheung is for the user to jiggle the needle, thereby aiding the segmentation based on difference images.

[0012] In addition, Cheung requires user interaction in switching among modes that differ as to the scope of search

for the needle. For example, a user reset of the search scope is needed when the needle is lost from view.

[0013] Cheung segmentation also relies on intensity-based edge detection that employs a threshold having a narrow range of effectiveness.

SUMMARY OF THE INVENTION

[0014] What is proposed herein below addresses one or more of the above concerns.

[0015] In addition to above-noted visualization difficulties, visualization is problematic when the needle is not yet deeply inserted into the tissue. The Cheung difficulty in distinguishing the needle from “needle-like” specular deflector is exacerbated in detecting a small portion of the needle, as when the needle insertion is just entering the field of view. In particular, Cheung applies a Hough transform to edge detection output of the ultrasound image. Specular structures competing with the needle portion may appear longer, especially at the onset of needle entry into the field of view. They may therefore accumulate more votes in the Hough transform, and thereby be identified as the most prominent straight-line feature in the ultrasound image, i.e., the needle.

[0016] Yet, the clinical value of needle detection is questionable if, to determine the needle’s pose, there is a need to wait until the needle is more deeply inserted. It would be better if the needle could be detected earlier in the insertion process, when the physician can evaluate its trajectory and change course without causing more damage and pain.

[0017] Reliable needle segmentation would allow automatic setting of the optimal beam steering angle, time gain compensation, and the image processing parameters, resulting in potentially enhanced visualization and clinical workflow.

[0018] In addition, segmentation and detection of the needle may allow fusion of ultrasound images with pre-operative modalities such as computed tomography (CT) or magnetic resonance (MR) imaging, enabling specialized image fusion systems for needle-based procedures.

[0019] A technological solution is needed to automatic needle segmentation that does not rely of the assumption that the needle is the brightest linear object in the image.

[0020] In an aspect of what is proposed herein, a classification-based medical image segmentation apparatus includes an ultrasound image acquisition device configured for acquiring, from ultrasound, an image depicting a medical instrument; and machine-learning-based-classification circuitry configured for using machine-learning-based-classification to, dynamically responsive to the acquiring, segment the instrument by operating on information derived from the image.

[0021] In sub-aspects or related aspects, US beam steering is employed to enhance the appearance of specular reflectors in the image. Next, a pixel-wise needle classifier trained from previously acquired ground truth data is applied to segment the needle from the tissue background. Finally, a Radon or Hough transform is used to detect the needle pose. The segmenting is accomplished via statistical boosting of wavelet features. The whole process of acquiring an image, segmenting the needle, and displaying an image with a visually enhanced and artifact-free needle-only overlay is done automatically and without the need for user intervention.

[0022] Validation results using ex-vivo and clinical datasets show enhanced detection in challenging ex-vivo and clinical datasets where sub-optimal needle position and tissue artifacts cause intensity based segmentation to fail.

[0023] Details of the novel, real time classification-based medical image segmentation are set forth further below, with the aid of the following drawings, which are not drawn to scale.

BRIEF DESCRIPTION OF THE DRAWINGS

[0024] FIG. 1 is a schematic and conceptual diagram of an exemplary real time classification-based medical image segmentation apparatus, in accordance with the present invention;

[0025] FIG. 2 is a conceptual diagram exemplary of the training, and clinical performance, of a statistical boosted classifier, and its use, in accordance with the present invention;

[0026] FIG. 3 is a conceptual diagram of a type of needle localization in accordance with the present invention;

[0027] FIG. 4 is a pair of flow charts of subroutines usable in a version of the present invention; and

[0028] FIG. 5 is a flow chart of a main routine demonstrating a clinical operation in accordance with the present invention.

DETAILED DESCRIPTION OF EMBODIMENTS

[0029] FIG. 1 depicts, by way of illustrative and non-limitative example, a real time classification-based medical image segmentation apparatus 100. It includes an ultrasound image acquisition device 104, such as a scanner. The device 104 includes a beamformer 108 and an ultrasound imaging probe 112. The probe 112 may be a linear array probe. It can be set with a field of view 116, in body tissue 120, that is defined by a lateral span 124 at any given imaging depth 128. The apparatus 110 can use the probe 112 to detect, in real time, entry of at least a portion 132 of a medical needle 136 into the field of view 116. The field of view 116 is defined by two boundary lines 140, 144. Detection of the needle 136 can occur with as little as 2.0 millimeters of the needle 136 being inserted into the field of view 116. This allows for earlier detection of the needle than available from existing methodologies. To improve the image of the needle 136, the current field of view 116 may change to a new field of view 148 for steering an ultrasound beam 152 into incidence upon the needle 136 at an angle of 90 degrees. The steered field of view 148 is shown in FIG. 1 with two boundary lines 156, 160. Beam steering to achieve normality with the needle 136 does not always require a change in the field of view 116. The improved image of the needle can be transferred to the overall image in the original field of view 116. This is done because the steering to achieve normality with the needle 136 slightly diminishes imaging quality in the resulting image overall, although enhancing visualization of the needle in particular. The apparatus 100 is designed for use in at least one of medical treatment and medical diagnosis. The needle 136 may, for example, be used to deliver medicament injected in an intra-body direction 164, as shown by the arrow. Biopsy, nerve block, and fluid aspiration are examples of other procedures where needle pose, position and movement are likewise monitored in real time.

[0030] The apparatus 100 further includes machine-learning-based-classification circuitry 168 that embodies a boosted classifier 172, such as Adaboost™ which is the most well-known statistical boosting algorithm.

[0031] For user interaction in monitoring via live imaging, the apparatus also includes a display 176 and user controls 180.

[0032] FIG. 2 conceptually portrays an exemplary version of training, and clinical performance, of the boosted classifier 172, and its use. To train the classifier 172, two-dimensional Log-Gabor wavelets (or “filters”) 204 are applied to a needle image 208. The needle image 208 has been acquired via beam steering, as discussed in more detail further below, and by utilizing ultrasound frequencies lower than those typically used in B-mode imaging. The output from applying the wavelets 204 is a set of wavelet feature parameters $F_{i,x,y}$ 212 for respective wavelet features F_i and respective pixels (x,y) 216 of the needle image 208. The ground truth $GT_{x,y}$ for each pixel 216, on whether it is part of the needle or part of the background is, or has been, determined. $F_{i,x,y}$ and $GT_{x,y}$ are part of a “weak classifier”, WK_1 . Multiple weak classifiers are combined, i.e., boosted 220, to provide a strong, or “boosted”, classifier. An alternative to this technique would be to use pixel intensity to decide whether the pixel 216 is needle or background. However, because of artifacts in the needle image 208, the intensity based thresholding is not robust enough to effectively classify the needle 136. The above steps in training the boosted classifier 172 are repeated for each of the needle images 208 in the training dataset, as represented in FIG. 2 by the broken downward line 224. The above-mentioned weak classifier WK_1 is built up by using the feature parameters $F_{i,x,y}$ each labeled with its respective ground truth $GT_{x,y}$. In particular, for a parameter from among $F_{1,x,y}$, the optimal threshold T_1 is found that delivers, in view of $GT_{x,y}$, the minimum classification error. The parameters to be thresholded essentially incorporate information about the shape of needle, angle of needle, texture and also the intensity. In addition, the training phase also provides information about what the needle doesn’t look like, i.e., what are the characteristics of the background image and muscle texture. All of the above processing is repeated for each feature F_2 through F_1 , as represented in FIG. 2 by the downward dot-dashed line 225. This is done to yield weak classifiers WK_2 through WK_1 , as represented in FIG. 2 by the downward dotted line 226, and to correspondingly yield optimal thresholds T_2 through T_1 . The weak classifiers WK_i are combined through appropriate weighting in forming a strong classifier SC which, during the clinical procedure, yields a binary output—“needle” 228 or “background” 232 for the pixel (x,y) 216. In effect, a set of weak hypotheses are combined into a strong hypothesis.

[0033] In the clinical procedure, the wavelets 204 are oriented incrementally in different angular directions as part of a sweep through an angular range, since 2D Log-Gabor filters can be oriented to respond to the spatial frequencies in different directions. At each increment, a respective needle image 208 is acquired at the current beam angle 236; the oriented wavelet 204 is applied, thereby operating on the image, to derive information, i.e., $F_{i,x,y}$ 212, from the image; and the above-described segmentation operates on the derived information. In the latter step, the boosted classifier 172 outputs a binary pixel-map 240 $M_{x,y}$ whose entries are apportioned between needle pixels and background pixels.

Depending on the extraction mode chosen by the operator, or depending on the implementation, the needle portion of the map **240** can be extracted **244a** and directly overlaid **252** onto a B-mode image, or a line detection algorithm such as a Radon transform or Hough transform (HT) **248** can be used to derive a position and angle of the needle **136**. In this latter case, a fresh needle image can be acquired, the background then being masked out, and the resulting, extracted **244b** “needle-only” image superimposed **256** onto a current B-mode image. Thus, the extraction mode can be set for “pixel map” or “ultrasound image.” It is reflected in steps **S432**, **S456** and **S556** which are discussed further below in connections with FIGS. **4** and **5**. Although a Log-Gabor filter is described above, other imaging filters such as the Gabor filter can be used instead.

[0034] FIG. **3** further illustrates exemplary details on the clinical procedure. The above-described incremental sweep **304** is, in the displayed example, through a range **308** of angles. Each increment **312** is shown, in FIG. **3**, next to the needle image **208** acquired at the corresponding beam angle. Any elongated, linear, and specular objects **314** in the image **208** are distinguished from the needle **136**, due to the robustness of the segmentation proposed herein. A segmentation **316** is run, by the boosted classifier **172**, on each needle image **208**, generating respective pixel maps **240**. The Hough transform **248** is applied to each pixel map **240**. The resulting line outputs **320** are summed **324**, as in summing the angle/offset bins. This determines an estimate of the offset, corresponding to the position, of the needle **136**. It also determines the angle **328** of the needle **136**. As mentioned herein above, the needle position and angle can be used in forming a displayable B-mode image with a “needle-only” overlay or, alternatively, the needle parts of the pixel maps **240** can be used provide needle pixels as the overlay.

[0035] Subroutines callable for performing the clinical procedure are shown in exemplary implementations in FIG. **4**.

[0036] In a first subroutine **400**, the wavelets **204** are oriented for the current beam angle **236** (step **S404**). The needle image **208** is acquired (step **S408**). The wavelets **204** are applied to the needle image **208** (step **S412**). The output is processed by the boosted statistical classifier **172** (step **S416**). The binary pixel map **240** is formed for the needle image **208** (step **S420**).

[0037] In a second subroutine **410**, the beam angle **236** is initialized to 5° (step **S424**). The first subroutine **400** is invoked (step **S428**), to commence at entry point “A” in FIG. **4**. If the pixel map **240** is being directly overlaid (step **S432**), the needle pixels and pixel-specific confidence values, for the needle pixels, are stored (step **S436**). Each of the weak classifiers WK_i returns, based on whether the threshold T_i is met, either -1 , representing background, or $+1$, representing needle. The strong classifier **SC** calculates a weighted sum of these values. If the sum is positive, the pixel **216** is deemed to be part of the needle **136**. Otherwise, the pixel **216** is deemed to be part of the background. However, the sum also is indicative of a confidence in the strong hypothesis. The closer the sum is to $+1$, the more confidence the decision of “needle” is accorded. The needle pixels, along with their corresponding confidence values, are recorded at this time for later generating a robust pixel map based on confidence values. Alternatively, the pixel map **240** might not be directly overlaid (step **S432**). In one embodiment, for

example, direct overlaying of the pixel map **240** may be intended as a display option alternative to a main process of overlaying a needle-only ultrasound image. If, accordingly, the pixel map **240** is not being directly overlaid (step **S432**), the output of the Hough transform **248** at the current beam angle **236** is added to that at the previous beam angle, if any, to create a running sum of the transform output (step **S440**). In either event, i.e., pixel map overlay or not, if the current beam angle **236** is less than 90° (step **S444**), the current beam angle is incremented (step **S448**) and return is made to the segmenting step **S428** (step **S452**). Otherwise, if the current beam angle **236** is 90° (step **S444**), processing again depends on whether the pixel map **240** is being directly overlaid (step **S456**). If the pixel map **240** is being directly overlaid (step **S456**), an optimal needle map is derived (step **S460**). In particular, the confidence values stored iteratively in step **S436** are combined. For example, each negative confidence value can be made zero. The confidence maps generated for the respective beam angles **236** are added to create a summed map. The confidence values are then normalized to a range of pixel brightness values. If, on the other hand, the pixel map **240** is not being directly overlaid (step **S456**), the Hough transform summed output **324** from step **S440** gives the needle offset (step **S464**). It also gives the angle **328** of the needle **136** (step **S468**).

[0038] FIG. **5** is, in the current example, the main routine of the clinical procedure. A needle-presence flag is initialized, i.e., cleared (step **S504**). The second subroutine **410** is called (step **S508**). It is determined whether or not a needle is present in the current field of view **116** (step **S512**). For instance, in the case of displaying the pixel map **240**, the number of needle pixels and optionally their confidence levels may be subject to thresholding to determine whether the needle **136** is present. In the case of displaying an ultrasound overlay, the line bin totals of the summed Hough transform **324** may be thresholded to determine if the needle **136** is present. If it is determined that the needle **136** is not present (step **S512**), and if the needle-presence flag is not set (step **S516**), a B-mode image is acquired (step **S524**). It is displayed (step **S528**). If imaging is to continue (step **S532**), return is made to the segmenting step **S508**. If, on the other hand, the needle-presence flag is set (step **S516**), it is cleared (step **S536**). The user is notified that the needle **136** is no longer onscreen (step **S540**), and processing branches back to B-mode acquisition step **S524**. In the case that the needle is determined to be present (step **S512**), and the needle-presence flag is not set (step **S544**), the user is notified of the entry of the needle into the displayed image (step **S548**) and the needle-presence flag is set (step **S552**). At this point, whether or not the needle-presence flag was, or has just been, set (steps **S544**, **S552**), the processing path depends on whether the pixel map **240** is to be used as an overlay (step **S556**). If the pixel map **240** is not to be used as an overlay (step **S556**), the needle angle **328** determined by the summed Hough transform **324** is used to steer the beam **152** to normality with the needle **136**, thereby providing better visibility of the needle (step **S560**). Via the steered beam **152**, a needle image **208** is acquired (step **S564**). Whether or not the pixel map **240** is to be used as an overlay, a B-mode image is acquired (step **S568**). A composite image is formed from the B-mode image and a superimposed needle-only image extracted from the needle image **208** or, in the case of a pixel map overlay, an extracted and superimposed set of the normalized confidence values from step **S456** or other

rendition of the pixel map **240** (step **S572**). The composite image is displayed (step **S576**). Periodically, i.e., iteratively after equally or unequally spaced apart periods of time, the needle **136** should be re-segmented as an update on its position and orientation. If the needle **136** is now to be re-segmented (step **S580**), processing returns to the segmenting step **S508**. Otherwise, if the needle **136** is not now to be re-segmented (step **S580**), but imaging is to continue (step **S584**), return is made to step **S556**.

[0039] The user notifications in steps **S540** and **S548** can be sensory, e.g., auditory, tactile or visual. For example, illuminations on a panel or display screen may, while in an “on” state, indicate that the respective mode of operation is active.

[0040] A needle-presence-detection mode **588** of operation corresponds, for example, to steps **S512-S532**.

[0041] A needle-insertion-detection mode **592** corresponds, for example, to steps **S512** and **S544-S552**.

[0042] A needle visualization mode **596** corresponds, for example, to steps **S556-S564**. One can exit the needle visualization mode **596**, yet remain in the needle-insertion-detection mode **592**. If, at some time thereafter, the needle-insertion-detection mode **592** detects re-entry of the needle **136** into the field of view **116**, the needle visualization mode **596** is re-activated automatically and without the need for user intervention. In the instant example, the needle-presence-detection mode **588** enables the needle-insertion-detection mode **592** and thus is always active during that mode **592**.

[0043] The above modes **588**, **592**, **596** may be collectively or individually activated or deactivated by the user controls **180**, and may each be incorporated into a larger overall mode.

[0044] Each of the above modes **588**, **592**, **596** may exist as an option of the apparatus **100**, user-actuatable for example, or alternatively may be part of the apparatus without any option for switching off the mode.

[0045] It is the quality and reliability of the needle segmentation proposed herein above that enables the modes **588**, **592**, **596**.

[0046] Although the proposed methodology can advantageously be applied in providing medical treatment to a human or animal subject, the scope of the present invention is not so limited. More broadly, techniques disclosed herein are directed to machine-learning-based image segmentation in vivo and ex vivo.

[0047] A classification-based medical image segmentation apparatus includes an ultrasound image acquisition device configured for acquiring, from ultrasound, an image depicting a medical instrument such as needle; and machine-learning-based-classification circuitry configured for using machine-learning-based-classification to, dynamically responsive to the acquiring, segment the instrument by operating on information derived from the image. The segmenting can be accomplished via statistical boosting of parameters of wavelet features. Each pixel of the image is identified as “needle” or “background.” The whole process of acquiring an image, segmenting the needle, and displaying an image with a visually enhanced and artifact-free needle-only overlay may be performed automatically and without the need for user intervention. The reliable needle segmentation affords automatic setting of the optimal beam

steering angle, time gain compensation, and the image processing parameters, resulting in enhanced visualization and clinical workflow.

[0048] While the invention has been illustrated and described in detail in the drawings and foregoing description, such illustration and description are to be considered illustrative or exemplary and not restrictive; the invention is not limited to the disclosed embodiments.

[0049] For example, the needle-insertion-detection mode **592** is capable of detecting at least part of the needle **136** when as little as 7 millimeters of the needle has been inserted into the body tissue, and, as mentioned herein above, 2.0 mm in the ultrasound field of view.

[0050] Other variations to the disclosed embodiments can be understood and effected by those skilled in the art in practicing the claimed invention, from a study of the drawings, the disclosure, and the appended claims. In the claims, the word “comprising” does not exclude other elements or steps, and the indefinite article “a” or “an” does not exclude a plurality. Any reference signs in the claims should not be construed as limiting the scope.

[0051] A computer program can be stored momentarily, temporarily or for a longer period of time on a suitable computer-readable medium, such as an optical storage medium or a solid-state medium. Such a medium is non-transitory only in the sense of not being a transitory, propagating signal, but includes other forms of computer-readable media such as register memory, processor cache and RAM.

[0052] A single processor or other unit may fulfill the functions of several items recited in the claims. The mere fact that certain measures are recited in mutually different dependent claims does not indicate that a combination of these measures cannot be used to advantage.

1. A classification-based medical-image identification apparatus comprising:

an ultrasound image acquisition device configured for acquiring, from ultrasound, an image depicting a medical instrument; and

machine-learning-based-classification circuitry configured for using machine-learning-based-classification to, dynamically responsive to said acquiring, segment said instrument by operating on information derived from said image.

2. The apparatus of claim 1, said circuitry comprising a boosted classifier, and being configured for using said classifier for the segmenting.

3. The apparatus of claim 2, said using comprising performing statistical boosting of parameters of wavelet features.

4. The apparatus of claim 1, configured for, via said device, dynamically performing, automatically, without need for user intervention, said acquiring repetitively, from different angles for corresponding depictions of said instrument, the segmenting of said depictions being dynamically responsive to the repetitive acquiring.

5. The apparatus of claim 4, further configured for performing said segmenting of said depictions depiction-by-depiction.

6. The apparatus of claim 4, said segmenting being performed incrementally, in a sweep, over a range of angles.

7. (canceled)

8. The apparatus of claim 4, said segmenting of said depictions using, in correspondence with said angles, different orientations of an imaging filter.

9. The apparatus of claim 4, further configured for dynamically determining, based on an outcome of said segmenting of said depictions, an orientation of said instrument.

10. The apparatus of claim 1, further comprising an ultrasound imaging probe, said apparatus being configured for dynamically determining, based on an output of the segmenting, an orientation of said instrument with respect to said probe.

11. The apparatus of claim 1, said instrument being a medical needle.

12. The apparatus of claim 10, said apparatus being designed for use in at least one of medical treatment and medical diagnosis.

13. (canceled)

14. (canceled)

15. (canceled)

16. (canceled)

17. The apparatus of claim 10, further comprising a display, said device comprising an ultrasound imaging probe having a field of view for spatially defining a span of dynamic visualizing of body tissue via said display, said apparatus being further configured with a needle-presence-detection mode of operation, said apparatus being further configured for, while in said mode, automatically, without

need for user intervention, deciding, based on output of the segmenting, that no needle is even partially present in said field of view.

18. (canceled)

19. (canceled)

20. (canceled)

21. The apparatus of claim 1, said circuitry embodying a classifier, for the machine-learning-based-classification, that has been trained both on pattern recognition of a needle and pattern recognition of body tissue.

22. (canceled)

23. The apparatus of claim 1, configured for, dynamically responsive to said acquiring, performing the deriving of said information from said image by operating on said image.

24. A computer-readable medium embodying a computer program for classification-based identification of a medical image, said program having instructions executable by a processor for performing a plurality of acts, among said plurality there being the acts of:

acquiring, from ultrasound, an image depicting a medical instrument; and

using machine-learning-based classification to, dynamically responsive to said acquiring, segment said instrument by operating on information derived from said image depicting a medical instrument.

* * * * *

一种基于分类的医学图像分割装置，包括：超声图像获取装置，被配置为从超声获取描绘诸如针的医疗器械的图像；基于机器学习的分类电路，被配置为使用基于机器学习的分类，动态地响应于获取，通过对从图像导出的信息（212）进行操作来分割仪器。可以通过小波特征的参数的统计增强（220）来完成分割。图像的每个像素（216）被识别为“针”或“背景”。获取图像，分割针以及显示具有视觉增强和无伪影的图像的全过程。仅针覆盖可以自动执行而无需用户干预。

