METHOD AND SYSTEM FOR STRUCTURAL INSPECTION

The present application claims priority to the Singapore patent application no. 10202106562P which is incorporated herein by reference in its entirety.

TECHNICAL FIELD

[1] The present disclosure relates to structural inspection, and more particularly to a method and system for performing structural inspection of large built structures.

BACKGROUND

[2] Performing inspection and diagnosis of walls and other structures is crucial for building maintenance and structural safety. Non-destructive inspection methods are preferred because they do not undermine the structural integrity of the structures under inspection. However, many challenges remain, for example, conventional non-destructive inspection methods require prior knowledge of the parameters of the surrounding structures and conditions.

SUMMARY

[3] In one aspect, the present disclosure describes a method of non-destructive structural inspection of a wall. The wall includes a wall medium. The method includes providing a first input to a first deep neural network, in which the first input is a two-dimensional (2-D) Ultra-Wide Band (UWB) signal matrix acquired by a pair of cross-polarized antennas, the pair of cross-polarized antennas being disposed on a probe over a moving distance across a surface of the wall. The method includes determining an imaging result based on a first output of the first deep neural network. The imaging result is determined independently of one or more predetermined parameters of the wall. The method includes determining a one-dimensional (1-D) UWB signal sequence based on the imaging result and the 2-D UWB signal matrix. The method includes acquiring a second output of a second deep neural network. The second deep neural network is configured to receive a second input based on the 1-D UWB signal sequence. The method includes responsive to the second output having one or more anomalies relative to a baseline component: determining a nature of an in-wall element corresponding to at least one of the one or more anomalies; and determining a

location of the at least one of the one or more anomalies based on the imaging result. The one or more anomalies of the in-wall element corresponds to at least one of: an in-wall defect, an in-wall structure, and a local difference in the wall medium.

[4] The method may include transmitting a plurality of UWB signals from a transmitter antenna toward the wall, the transmitter antenna being disposed on the probe such that the transmitter antenna is parallel to one of the pair of cross-polarized antennas and such that the transmitter antenna is perpendicular to another of the pair of cross-polarized antennas, such that the probe is operable as a monostatic probe. The method may include: separating the 1-D UWB signal sequence into a co-polarization signal and a cross-polarization signal, wherein the co-polarization signal and the cross-polarization signal are configured as the second input to the second deep neural network. The imaging result is determined independently of a speed at which the probe is moved over the moving distance. The method may be configured such that the co-polarization signal and the cross-polarization signal respectively received by the pair of cross-polarized antennas are used to determine the respective polarization direction of the 1-D UWB signal.

[5] The determining of the nature of the in-wall element may include one of the following: identifying a material composition of the in-wall element, diagnosing a condition of the in-wall element, and a combination thereof. The method may include diagnosing a structural health of the wall based on at least one of the following: the nature of the at least one in-wall element, a nature of the wall medium, a change in the nature of the at least one in-wall element, a change in the nature of the wall medium, and any combination thereof.

[6] The 2-D UWB signal matrix may include a plurality of selected time series signal, wherein each of the plurality of selected time series signal is selected from a plurality of antenna time series signal received by the pair of cross-polarized antennas. Each of the plurality of time series signal may correspond to a position of the pair of cross-polarized antennas relative to the starting point and/or the moving distance.

[7] The first deep neural network may include an encoder module and a decoder module, wherein the encoder module is configured to contract the 2-D UWB signal matrix into an intermediate matrix, and wherein the decoder module is configured to upscale the intermediate matrix to determine the imaging result. The decoder module may include a

plurality of up-sampling levels in a series connection, and wherein each of the plurality of up-sampling levels is configured to receive an input from the encoder module.

[8] The second deep neural network may include a material identifier module configured to determine the material. The second deep neural network may further include an environmental discriminator module configured to remove an environmental influence corresponding to the wall medium.

[9] The first deep neural network and the second deep neural network may be trained independently of one another. The second deep neural network may be trained via an adversarial learning method.

[10] The probe may be moved over the moving distance at an arbitrary speed. The wall medium may include a non-homogenous material. The wall medium may include a plurality of materials.

[11] In another aspect, the present disclosure describes a system for non-destructive structural inspection of a wall, the wall including a wall medium, the system including: a probe movable over a moving distance across a surface of the wall, the probe including a pair of cross polarized antennas; and a controller in signal communication with the probe, the controller being configured to perform the method according to any described above.

[12] The probe may be configured to be held by hand by a user to move the probe between a starting point and a terminal point to determine one or both of the following: a position of the in-wall element relative to the starting point and a depth of the in-wall element relative to the surface of the wall. The system may further include a user interface configured to receive the first output and the second output, the user interface being configured to output at least one of the following: the position of the in-wall element, the depth of the in-wall element, a material composition of the in-wall element, a condition of the in-wall element, a structural health determination of the wall, and any combination thereof. Preferably, the probe is configured as a monostatic probe.

BRIEF DESCRIPTION OF DRAWINGS

[13] Fig. 1A is a schematic diagram of a system for structural inspection according to an

embodiment of the present disclosure;

[14] Fig. 1B is a schematic diagram of a probe of the system of Fig. 1A;

[15] Fig. 2 shows an example of a 2-D UWB signal matrix;

[16] Figs. 3A and 3B are images obtained for different estimated probe movement speeds;

[17] Figs. 3C and 3D are images showing the effect of the estimated relative permittivity of the wall;

[18] Fig. 4A shows an example of a wall with in-wall elements embedded therein;

[19] Fig. 4B is an example of an image of Fig. 4A, based on imaging results obtained according to one embodiment of the present disclosure;

[20] Fig. 5 is a schematic diagram of a method of structural inspection according to the system of Fig. 1A;

[21] Fig. 6 is a schematic diagram of a first part of the method of Fig. 5;

[22] Fig. 7 is a schematic diagram of a second part of the method of Fig. 5;

[23] Figs. 8A and 8B are examples of extracting one “column” out of a 1-D UWB signal matrix and separating it into a co-polarization signal and a cross-polarization signal;

[24] Fig. 9A shows an example of an image of an in-wall element, based on imaging results determined by the system of Fig. 1A;

[25] Fig. 9B shows an example of an image result of an in-wall element, based on imaging results determined by a conventional system;

[26] Fig. 10A shows a horizontal distance error of the imaging result of Fig. 9A;

[27] Fig. 10B shows a horizontal distance error of the imaging result of Fig. 9B;

[28] Fig. 11A shows a depth error of the imaging result of Fig. 9A;

[29] Fig. 11B shows a depth error of the imaging result of Fig. 9B;

[30] Fig. 12A and 12B illustrate evaluation results of the system of Fig. 1A in relation to the impact of water content in the wall medium (increased from 0 g/m^3 to 100 g/m^3) on the accuracies of estimating both horizontal distance and depth;

[31] Figs. 13A and 13B illustrate evaluation results of the system of Fig. 1A in relation to the impact of depth of the in-wall structure on the accuracies of estimating both horizontal distance and depth;

[32] Figs. 14A and 14B illustrate evaluation results of the system of Fig. 1A in relation to the impact of the moving speed of the probe on the accuracies of estimating both horizontal distance and depth;

[33] Figs. 15A and 15B illustrate evaluation results of the system of Fig. 1A in relation to the impact of different material of in-wall structures on the accuracies of estimating both horizontal distance and depth;

[34] Figs. 16A to 16D illustrate confusion matrices for characterizing the material determination performance under different wall mediums;

[35] Figs. 17A and 17B illustrate the accuracies of material determination and status diagnosis in relation to the depth of in-wall structures;

[36] Figs. 18A and 18B illustrate results of material determination and status diagnosis performance due to varying water content in the wall medium;

[37] Fig. 19A is an image showing an example of a wall with in-wall elements such as cracks;

[38] Fig. 19B is a composite of images based on imaging results of the wall of Fig. 19A;

[39] Fig. 20A shows an example of a multi-material wall medium; and

[40] Fig. 20B is an image based on imaging results of the wall of Fig. 20A.

DETAILED DESCRIPTION

[41] Reference throughout this specification to “one embodiment”, “another embodiment”, or “an embodiment” (or the like) means that a particular feature, structure, or characteristic described in connection with the embodiment is included in at least one embodiment. Thus, the appearance of the phrases “in one embodiment” or “in an embodiment” or the like in various places throughout this specification are not necessarily all referring to the same embodiment. Furthermore, the described features, structures, or characteristics may be combined in any suitable manner in one or more embodiments. In the following description, numerous specific details are provided to give a thorough understanding of the embodiments. One skilled in the relevant art will recognize that the various embodiments may be practiced without one or more of the specific details, or with other methods, components, materials, etc. In other instances, some or all known structures, materials, or operations may not be shown or described in detail to avoid obfuscation.

[42] The word “exemplary” is used herein to mean “serving as an example, instance, or illustration.” Any embodiment described herein as “exemplary” is not to be construed as necessarily preferred or advantageous over other embodiments. As used herein, the singular ‘a’ and ‘an’ may be construed as including the plural “one or more” unless apparent from the context to be otherwise.

[43] Terms such as “first” and “second” are used in the description and claims only for the sake of brevity and clarity, and do not necessarily imply a priority or order, unless specified. The terms "about" and "approximately" as applied to a stated numeric value encompasses the exact value and a reasonable variance as will be understood by one of ordinary skill in the art, and the terms “generally” and “substantially” are to be understood in a similar manner, unless otherwise specified.

[44] In the present disclosure, the terms “machine learning”, “neural network”, “artificial intelligence”, “deep learning”, and “neural network” may be used interchangeably. The term “deep neural network (DNN)” may generally refer to, but is not limited to, one or multiple ones of the following: a supervised learning model, an unsupervised learning model, a regression model, a classification model, a neural network model, a deep learning model, a decision tree model, a support vector machine model, a naïve Bayes model, a clustering model, a principal component analysis (PCA) model, etc., and/or any combination thereof.

[45] The term “Ultra-wide Band (UWB)” may generally refer to radio-frequency waves operating over a frequency spectrum from about 3.1 GHz (gigahertz) to about 10.6 GHz, and characterized by a channel bandwidth of about or over 500 MHz (megahertz), for example. It may be appreciated that radio waves outside of the frequency spectrum and/or has a different channel bandwidth which are suitably functional with the methods and systems as disclosed, is also within the scope of the present disclosure. The term “impulse radio” refers to short duration radio wave pulses.

[46] The term “wall”, “structure”, “built structure”, and the like are used interchangeably in the present disclosure to refer to a part of a built structure, including but not limited to, buildings, tunnels, bridges, etc. The term “in-wall elements” refers generally to one or more element inside the structure, and may include “in-wall structures” and/or “in-wall defects”. “In-wall structures” may include, but are not limited to, structural or supportive elements in a wall, such as rebars (reinforcing bars), pipes, steel grids, etc. “In-wall defects” may include, but are not limited to, potential or actual structural weaknesses such as cracks, voids, presence of material accumulation, water ingression, etc. An “in-wall defect” may also include a local difference in the wall medium. For instance, material composition changes over time may occur at a relatively localized or small section of the wall without showing visible cracks. Changes may result over time from wear-and-tear, water seepage, infiltration of chemicals, mold or fungus growth, etc.

[47] It will be understood that “in-wall structures” may themselves be sources of “in-wall defects”, for example, if the rebar has become corroded, etc. In actual practice, using conventional methods, it is difficult to distinguish between in-wall elements that are serving as strengthening elements and in-wall elements that may be potential or actual areas of structural weaknesses. This is only one reason why non-destructive inspection of structural health remains a challenge in the field of structural inspection of built structures or building inspection.

[48] Conventional non-destructive methods of inspecting a wall typically require prior knowledge of the building plans and the material properties of the wall as-built. Theoretically, knowledge of the original/designed material properties, e.g., the permittivity of the wall material would provide a means of comparing calculated/measured values and

the original/designed values, such that a difference or discrepancy between the two could be used as an indication of a deterioration in the wall material. In actual practice, information of the original/designed material properties may not be available. In some cases, the original material properties of the as-built structure may not have complied with the approved design.

[49] In addition, the wall medium surrounding any in-wall element is itself often characterized by inhomogeneity. The term "wall medium" refers to the material forming the substantive bulk of the wall. Such variations can affect the detection of in-wall elements. For example, different parts of a concrete wall may have different water content in the concrete wall medium itself. In relatively humid tropical climates, the same concrete structure may have different parts exposed to different amounts of sunlight and/or rain and other weather elements, such that over time the different parts of the concrete have very different water content. In extreme cases, an in-wall element may be mistaken for part of the wall medium such that a potential source of structural weakness is overlooked. The varying wall medium may result in "false measurements", leading to erroneous or inaccurate assessment of the structural health of the wall. Even if the original building plans are available and the location of in-wall structures (such as rebars) can be identified with pinpoint accuracy, conventionally it remains a challenge to determine the extent of structural health because of such "false measurements". In examples where the wall includes a multi-material wall medium, such as a layered wall with a concrete layer and a wood layer, the problem of erroneous or inaccurate results is aggravated. One skilled in the art would therefore understand that information from other technical fields where the wall medium may be assumed to be essentially homogenous (e.g., air, ocean) may not be applicable to the present technical problem.

[50] One aspect of the present disclosure relates to an Ultra-Wide Band Impulse Radio (IR-UWB) system 100 and method 700 for non-destructive structural inspection (also referred to as "SiWa" or "See into Walls via deep UWB radar"). Fig. 1A schematically illustrates a system 100 for detecting an in-wall element 73 in a wall 71, according to one embodiment of the present disclosure. The in-wall element 73 may be one or more in-wall defect 72, including but not limited to a crack in the wall medium 70, and/or one or more in-wall structure 74, including but not limited to a rebar. The in-wall element 73 may be

embedded in the wall medium 70. The wall medium 70 may be mostly formed of a material such as concrete and/or a composite material.

[51] The system 100 may include a probe 200 and a controller 300. The probe 200 and the controller 300 are configured to be in operable signal communication with one another. The controller 300 may be coupled with a user interface 302 configured to display or otherwise output data and/or information. As illustrated schematically in Fig. 1B, the probe 200 includes receiver antennas, such as a pair of cross-polarized antennas 210/220 and a transmitter antenna 230. The pair of cross-polarized antennas 210/220 may include a first receiver antenna 210 disposed along a first axis 212 and a second receiver antenna 220 disposed along a second axis 222. The first axis 212 is configured orthogonal to the second axis 222, which enables the receiver antennas 210/220 to be cross-polarized. The transmitter antenna 230 may be arranged along a transmitter axis 232. Preferably, the transmitter axis 232 is disposed parallel to one of the receiver antennas 210/220, for example, the transmitter antenna 230 may be parallel to the first receiver antenna 210. In some embodiments, the probe 200 is configured to be portable, i.e., configured to be held in one hand by a user 80 when the system 100 is in use. According to one embodiment of the method 700 proposed herein, the probe 200 may be moved relative to the wall medium 70 by hand, i.e., at an arbitrary speed (swiping speed). The swiping speed or the speed at which the user 80 moves the probe 200 need not be predetermined or limited to a particular range of values.

[52] The conventional bistatic radar operates on the basis that the transmitter and the receiver are physically spaced apart by a distance (e.g., with a stationary transmitter), and is conventionally preferred for delivering more abundant target feature information than a monostatic radar system. In contrast, the probe 200 of the present disclosure is preferably configured as a monostatic probe. In some embodiments of the present disclosure, the transmitter antenna 230 and the receiver antennas 210/220 are disposed proximal to each other. In some embodiments, the monostatic probe 200 of the present disclosure may be configured with the transmitter antenna 230 and both of the receiver antennas 210/220 co-located and disposed on the same handheld device. This configuration enables wall inspection to be performed on wall medium with only one accessible side/surface, such as a wall medium of a tunnel. It can be appreciated that the present system 100 represents a departure from the conventional bistatic radar architecture, and yet is capable of providing

more meaningful results.

[53] It is understood that although the system 100 is described as including one controller 300, it is not outside the scope of the present disclosure for one or more embodiments described herein to be executed by more than one controller. The term "controller" is used herein to refer to one or more processor, or a programmable device, configurable to execute code/programs/instructions. In some embodiments, the controller 300 may embody a set of computer-implementable instructions. The set of computer implementable instructions may be stored in a non-transitory computer-readable storage, and executable by a processor in a computing device. In some embodiments, the controller 300 may be embodied in an integrated circuit which forms part of a portable device. The controller 300 is configured to control the transmitter antenna 230 to transmit one or more UWB signals (pulses), for example, towards the wall 71 to be inspected. The UWB signals reflect off the wall medium 70 as well as any in-wall elements 73, and the reflected signals are captured by the receiver antennas 210/220.

[54] Fig. 2 graphically illustrates the two-dimensional (2-D) UWB signal matrix that can be acquired by the controller 300 from the probe 200. Assuming there are K number of targets disposed in a wall, in which each of the targets serves as a point scatterer of the UWB signals, and a UWB signal takes the form of a Gaussian pulse:

$$s(t) = \alpha_{tx} exp(-t^2/2\sigma^2) \quad (1)$$

This signal is modulated onto a carrier such that:

$$x(t) = s(t) \cdot \cos(2\pi f_c t) \quad (2)$$

where α_{tx} is the pulse amplitude, σ^2 is the variance defined by a -10 dB bandwidth, and f_c is the carrier frequency.

[55] The tx signal travels to the k-th target and the echo from the k-th target scatters back after a time delay $\tau_k = \frac{2r_k}{c}$, where r_k is the range to the k-th target, and c is the speed of light in the wall medium. The rx signal becomes:

$$r(t) = \sum_{k=1}^{K} \beta_k s(t - \tau_k) \cdot \cos\big(2\pi f_c (t - \tau_k)\big) + n(t) \quad (3)$$

where β_k is a scaling term attributed to propagation and reflection, and $n(t)$ represents the Gaussian noise.

[56] As the probe 200 repeatedly transmits and receives UWB signals (pulses) at regular intervals, a series of one-dimensional (1-D) sequences as shown in Equation (3) above can be obtained. By stacking the 1-D signals, the 2-D signal matrix of Fig. 2 can be obtained. Equation (3) may be generalized as $\boldsymbol{r}(x,t)_{z=0}$ to represent the 2-D signal matrix, where x denotes the moving distance of the radar, t represents the range dimension. The probe 200 remains on the surface 75 of the wall 71 and thus $z = 0$. For an in-wall element 73 that extends in an x-z plane substantially parallel to the movement (A-B) of the probe 200, the in-wall element 73 may be described as a scatterer that extends in the x-z plane, and the summation in Equation (3) may be replaced by an integration. A scatterer extending out of the x-z plane (imaging plane) may be approximated as a point scatterer.

[57] The location of an in-wall element cannot be easily determined from the raw data or the received / reflected UWB signals. As the probe 200 is moved across the surface 75 of the wall, the distance from the probe 200 to an in-wall element 73 located at (x_0, z_0) first decreases and then increases. In the 2-D signal matrix, a trace of the Gaussian pulse forms a hyperbola as shown in Fig. 2. In other words, a point scatterer emerges as a hyperbola and the exact position of the in-wall element 73 becomes difficult to pinpoint. In actual implementation, the signals received by the receiver antennas 210/220 are complicated by the fact that the actual swiping speed at which the user moves the probe 200 is unknown and variable, and that the reflected signals from different in-wall elements may be mixed up together. If the wall medium itself is highly non-homogenous, the signal reflected by an in-wall element may be obfuscated or indistinguishable from the signals reflected by a part of wall medium.

[58] To illustrate the nature of the raw data received by the receiver antenna, conventional images based on imaging results obtained by applying a conventional Range Migration Algorithm (RMA) to the raw data are shown in Figs. 3A to 3D. Fig. 3A shows the image obtained using the conventional RMA method where the user swiped a probe over a wall at a known swiping speed or probe movement speed of 2 cm/s (centimeters per second), and the estimated swiping speed matches the true speed. Fig. 3B shows the image based on the

same raw data as Fig. 3A, but where the swiping speed is estimated to be 1 cm/s, hence the estimated swiping speed differs from the true speed. Figs. 3A and 3B differ significantly from one another, showing different numbers of in-wall structures and different positions/locations for the in-wall structures. That is, the imaging results of the convention method are not independent of the swiping speed.

[59] Fig. 3C shows an image based on the conventional RMA imaging results where the actual relative permittivity of the wall medium is known to be 9, and the estimated relative permittivity of the wall medium matches the actual relative permittivity. Fig. 3D shows the image according to conventional RMA imaging results based on the same raw data as Fig. 3C, but where the relative permittivity of the wall medium is assumed unknown and hence estimated to be 7. In this case, the estimated relative permittivity of the wall medium differs from the actual relative permittivity. The imaging results of Fig. 3D are too blurred to pinpoint the presence or the location of the in-wall elements. One skilled in the art would therefore appreciate that application of conventional methods such as RMA requires prior knowledge of the actual parameters. The actual parameters are often unknown. In fact, the actual parameters may vary extensively depending on the way the user swipes the probe, or if the wall medium is non-homogenous and/or has suffered deterioration over the course of use.

[60] To aid understanding, the system 100 in operation and a method 700 of structural inspection using the system 100 will be described with reference to experiments conducted using a wall specimen as shown in Fig. 4A. The wall 71 has five in-wall elements 73 in the form of rebars, embedded spaced apart at intervals of 5 cm (centimeters) and 10 cm respectively, at a depth of about 3 cm from the surface 75 of the wall 71. The wall medium 70 is concrete. The probe 200 is swiped by hand over a distance of 40 cm along the surface 75. In the present method 700, the swiping speed at which the user 80 moves the probe 200 does not need to be noted, and no mechanisms to ensure a steady swiping speed is required. The relative permittivity of the wall medium 70 is also not required for the purpose of implementing the system 100. Fig. 4B shows the image or the imaging results obtained using the system 100 and method 700 proposed herein.

[61] The probe 200 is configured to repeatedly transmit and receive UWB signals at

regular intervals as the user 80 swipes the probe 200 across the surface 75. As shown in Fig. 5, the controller 300 is configured to receive the resulting plurality of UWB time series signals 400 from the pair of cross-polarized antennas 210/220 (710). In some embodiments, the controller 300 stacks the UWB time series signals 400 to construct a 2-dimensional (2-D) UWB signal matrix 410 from the UWB time series signals 400. In other embodiments, the UWB time series signal 400 captured by the cross-polarized antennas may be first preprocessed before being stacked and constructed into a 2-D UWB signal matrix 410 receivable by the controller 300. In some embodiments, each of the plurality of UWB time series signals 400 received by the controller 300 corresponds to a position of the pair of cross-polarized antennas 210/220 between a starting point A and a terminal point B. In other words, the 2-D UWB signal matrix may include a plurality of selected time series signals, wherein each of the plurality of selected time series signals is selected from a plurality of antenna time series signals provided by the pair of cross-polarized antennas 210/220. Each of the plurality of time series signals may correspond to a position (x) of the pair of cross-polarized antennas 210/220 relative to the starting point A and/or the moving distance 88.

[62] The controller 300 is configured to provide the 2-D UWB signal matrix 410 as a first input to a first deep neural network (DNN) 310. Referring now to Fig. 6, according to one embodiment of the present disclosure, the first DNN 310 includes an encoder module 312 and a decoder module 314. The encoder module 312 may be a contraction network configured as a convolutional neural network (CNN) having a plurality of neural network levels. The encoder module 312 may be configured to distill one or more feature representations from the 2-D UWB signal matrix 420 at each of the neural network levels, and to contract the 2-D UWB signal matrix 420 into an intermediate matrix 415. In some embodiments, the intermediate matrix 415 is a latent (feature) vector. The decoder module 314 may be configured to upscale the intermediate matrix 415 to generate an imaging result. The intermediate matrix 415 may have a reduced dimensional feature in comparison to the 2-D UWB signal matrix 420 and/or the imaging result. The intermediate matrix 415 may be characterized by fewer dimensions relative to each of the 2-D UWB signal matrix 420. The intermediate matrix 415 may be characterized by fewer dimensions relative to the imaging results generated by the decoder module 314. The decoder module 314 may include a plurality of up-sampling levels 314a/314b/314c in series connection. As an example, each

of the up-sampling levels 314a/314b/314c may include ResNet blocks with pooling operators replaced with up-sampling operators. This allows the respective resolution of intermediate images to be gradually increased. In some embodiments, the feature representations distilled at each level of the encoder module 312 are fed into respective up-sampling levels 314a/314b/314c of the decoder module 312. A skip connection 313a/313b/313c from a corresponding level of the encoder module 312 may be provided to each up-sampling levels 314a/314b/314c of the decoder module 312. Each up-sampling levels 314a/314b/314c of the decoder module 312 includes an up-convolutional layer and an up-sampling layer stacked together, and forwarded to the next up-sampling level. A final level 314d of the decoder module 312 gathers the intermediate images and generates an imaging result 420. In one example, the final level 314d may include a ResNet block connected with a convolutional layer. The imaging result 420 provides a 2-D graphical representation corresponding to the structure of the wall 71. The controller 300 is configured to provide the imaging result 420 and/or to output the respective location of the one or more in-wall elements 73 embedded in the wall medium 70 (422). The location may be defined or described in terms of position and/or depth coordinates (e.g., with reference to the x-z plane).

[63] In other words, the first DNN 310 is configured to generate an imaging result 420 The imaging result 420 may be representative of a position of the in-wall element 73. The imaging result 420 provides information 422 including a position of the in-wall element 73 (e.g., relative to the starting point A) and a depth of the in-wall element relative to the wall surface 75.

[64] As shown in Fig. 5 and Fig. 7, the controller 300 is configured with a signal extractor 320. The signal extractor 320 is configured to acquire the imaging result and the 2-D UWB signal matrix 410 from the two orthogonally polarized antennas 210/220. The signal extractor 320 may be configured to select or extract selected one-dimensional (1-D) UWB signal sequences from the imaging results 420 and the transmitted/received UWB signals or 2D UWB signal matrix 410. The term “1-D UWB signal sequence” may refer to a single dimension signal array. The signal extractor 320 may be configured to obtain positions of the one or more in-wall elements 73 by applying a Constant False Alarm Rate (CFAR) algorithm. In some embodiments, extracting the 1-D UWB signals 430 includes taking the

signal with the highest Signal-to-Noise (SNR) ratio among those close to the obtained positions.

[65] In some embodiments, the controller 300 is configured to separate the 1-D UWB signal 430 into a co-polarization signal 432 and a cross-polarization signal 434. The co-polarization signal 432 may correspond to a polarization direction of one of the cross-polarized antennas, such as the first receiver antenna 210. The cross-polarization signal 434 may correspond to another polarization direction of the cross-polarized antennas, such as that of the second receiver antenna 220. The co-polarization signal 432 and the cross-polarization signal 434 respectively received by the pair of cross-polarized antennas 210/220 may be used to determine a respective polarization direction of the 1-D UWB signal 430.

[66] One aspect of the 1-D UWB signals is illustrated with the aid of Figs. 8A and 8B which are examples of extracting one "column" out of a 1-D UWB signal matrix and separating it into a co-polarization signal and a cross-polarization signal. The received UWB signals may be divided by the spectrum of the transmitter UWB signal (Gaussian pulse) to obtained respective reflection coefficients for the received UWB signal in the co-polarization direction and in the cross-polarization direction. Fig. 8A shows the co-polarization coefficients and the cross-polarization coefficients for a rebar that is buried in a concrete wall. Fig. 8B shows the co-polarization coefficients and the cross-polarization coefficients for a polyvinyl chloride (PVC) pipe buried in the same concrete wall at the same depth as the rebar. These waveforms are obtained under ideal test conditions in the laboratory. While the different materials show different waveforms, it has also been found that similar materials buried at different depths from the surface of the wall also show differences in the waveforms. Additionally, the waveforms are also the product of environmental influences, including influences from the wall medium.

[67] As illustrated in Fig. 5 and Fig 7, the controller 300 is configured with a second deep neural network (DNN) 330. The controller 300 is configured to provide the 1-D UWB signal as a second input to the second DNN 330. In some embodiments, the 1-D UWB signals (sequence) 430 may be separated into a co-polarization signal 432 and a cross-polarization signal 434 prior to input to the second DNN 330. In some embodiments, the 1-D UWB

signal matrix 430 is to be fed directly into the second DNN 330. The second DNN 330 may include a feature extractor 332, a material identifier module 334, and an environmental discriminator module 336. In some embodiments, the feature extractor 332 may include a 1-D convolutional layer and a ResNet block. The material identifier module 334 may include multiple linear layers. Similarly, the environmental discriminator module 336 may also include multiple linear layers.

[68] In some embodiments, the feature extractor 332 may be configured to receive the 1-D UWB signal sequence 430 which includes different polarization directions, e.g., the co-polarization signal 432 and the cross-polarization signal 434. The feature extractor 332 may be configured to extract features from the 1-D UWB signal sequence 430 to be fed into the material identifier module 334 and the environmental discriminator module 336. The environmental discriminator module 336 is configured to remove an environmental influence corresponding to the wall medium 70. The second DNN 330 may be trained to predict material class labels using samples collected from different environments. During a training process, the classification accuracy of the second DNN 330 may be improved by or trained via an adversarial learning method by negating a loss function. The second DNN 330 may be trained to predict material class labels using the samples collected from different environments. The loss function may be achieved by reversing the gradient during a backpropagation process with the Gradient Reversal Layer (GRL) 335 during training. In order to prevent conflicting gradients, the backpropagation may be augmented by projecting the gradients of the feature extractor 332 and the material identifier module 334 onto each other. This contributes to the suppression of unrelated features and prevents the second DNN 330 from overfitting to specific environmental influences. The second DNN 330 may be configured as an effective classifier which is robust to environmental influences, or in other words, relatively unaffected by the wall medium material during in-wall structure material determination. As a classifier, the second DNN 330 maps the input 1-D UWB signal sequences 430 space to a label space which is a finite set indicating materials of different conditions (e.g., leaked PVC pipe, non-corroded rebar, etc.).

[69] In some embodiments, a second output of the second DNN 330 may include one or more anomalies, in which the one or more anomalies are determined with reference to a baseline component. An anomaly refers to a deviation from the baseline component of the

second output. In an example of a substantially uniform wall with no in-wall element, the second output may be described as having a baseline component with no anomalies. Responsive to the second output having one or more anomalies, the second DNN 330 may determine a nature of an in-wall element corresponding to at least one of the one or more anomalies. One or more of the anomalies may correspond to one or more of an in-wall defect, an in-wall structure, a local difference in wall medium composition, etc. The system 100 may be configured to accurately determine the location of the in-wall element upon determining the presence of the in-wall element. The location of the in-wall element may be determined based on the imaging result, and may be defined or described in terms of the position (relative to the moving distance) and the depth (relative to the wall surface). Responsive to the second output having no anomalies, the second DNN 330 determines an absence of in-wall element in the wall. The second DNN 330 may also be configured to predictively identify a material composition of the in-wall element 73. In this example, the material composition of the rebars will be predictively determined (440). The second DNN 330 may be configured to concurrently or subsequently predictively diagnose a health state of the in-wall element, the wall medium, and/or the wall as a whole (442).

[70] The system 100 is configured for non-destructive structural inspection of a wall, such that in use, the probe 200 is movable over a moving distance 88 across the surface 75 of the wall 71, without the need to cut into the wall to reveal what may be embedded in the wall 71 or wall medium 70. The probe 200 may be moved from a starting point A, and the starting point A may serve as a reference for localizing (i.e., identifying the position of) a part of the wall 71 or any in-wall element 73 found in the wall 71. The probe 200 includes a pair of cross polarized antennas 210/220. The controller 300 is configured to be in signal communication with the probe 200, in which the controller 300 being is configured to perform the method 700 according to any described above. The probe 200 may be configured to be held by hand by a user 80, i.e., portable. In use, the user may move the probe 200 between a starting point A and a terminal point B to determine one or both of the following: a position (x) of the in-wall element 73 relative to the starting point A and a depth (z) of the in-wall element 73 relative to the surface 75 of the wall 71. The system 100 may further include a user interface 302 configured to receive the first output from the first DNN and the second output from the second DNN. The user interface 302 may be

configured to output at least one of the following: the position of the in-wall element 73, the depth of the in-wall element 73, a material composition of the in-wall element 73, a condition of the in-wall element 73, a structural health determination of the wall 71, and any combination thereof.

[71] Figs. 9A to 11B compare the results provided by embodiments of the present system 100 and method 700 against the results of a conventional frequency-domain Range Migration Algorithm (RMA) system.

[72] Figs. 9A and 9B are images corresponding to imaging results provided by the present system 100 (Fig. 9A) and the conventional RMA system (Fig. 9B) respectively. As described above, it is difficult to determine the position and other information of the in-wall elements from such images. To measure the imaging quality quantitatively, it is not possible to employ conventional SNR as there is no reference image for comparison. Therefore, the blind/reference-less Image Spatial Quality Evaluator (BRISQUE) score was adopted for comparison. The BRISQUE method compares an imaging result to a default model computed from images of natural scenes with similar distortions; it yields a unitless score between 0 and 100, with a smaller score value indicating a better perceptual quality. The BRISQUE scores of imaging results from the present system 100 and conventional system (RMA) are shown in Table 1. As evident from Table 1, the present system 100 consistently yields a lower score regardless of the material composition of the wall medium, indicating an improved performance by the present system 100 over the conventional system.

Table 1: BRISQUE scores

BRISQUE	Concrete	Brick	Wooden	Drywall
System 100	40.24	45.28	34.8	38.57
Conventional (RMA system)	45.44	49.34	40.15	40.84

[73] Figs. 10A and 10B describe examples where the moving distance is oriented horizontally. It will be understood that reference to “horizontal distance”, “horizontal distance error”, “horizontal direction”, etc are only illustrative and non-limiting examples

of “moving distance”, “moving distance error”, “moving distance direction”, etc respectively. Fig. 10A illustrates the Cumulative Distribution Functions (CDFs) of the horizontal distance error when the positions of in-wall elements are determined using the present system 100, for samples in which the in-wall elements are embedded in the different wall mediums of concrete, drywall, wood, and brick. Fig. 10B illustrates the Cumulative Distribution Functions (CDFs) of horizontal distance error when the positions of the in-wall elements are determined using the convention RMA system. In Fig. 10B, the solid lines show the cases where the parameters (i.e., the permittivity of the wall and the swiping speed of the probe) are known, and the horizontal positions can be calculated according to theory. In Fig. 10B, the dashed lines represent the values obtained using the conventional RMA system and where the parameters are unknown and estimated such that the parameters have errors within ±20%. As observed from Fig. 10A, the median errors of the present system 100 are 0.2 cm, 0.4 cm, 0.7 cm, and 0.7 cm for drywall, wooden wall, brick wall, and concrete wall, respectively. These errors are in line with common understanding as concrete and brick walls cause higher attenuation to radio frequency signals, and hence result in larger localization errors. In contrast, the median errors increase to 0.3 cm, 0.4 cm, 0.5 cm, and 3.6 cm in the case of the conventional RMA system where parameters are unknown and at best only estimated (as is the case in many real-life situations). In the case of the conventional RMA system, the curves (dashed lines) have very long tails, indicating a rapid degrading of performance.

[74] Similar observations of rapidly degrading performance can be made of the depth errors, as illustrated in Figs. 11A and 11B. Fig. 11A illustrates the Cumulative Distribution Functions (CDFs) of the depth error (error in determining the depth, i.e., the distance from the surface of the wall to the in-wall element) in different wall mediums for the present system 100. The depth errors for the conventional RMA system is shown in Fig. 11B. The solid lines in Fig. 11B show the cases where the parameters are known. The dashed lines in Fig. 11B show the cases where the parameters are unknown and are at best estimated. It can be seen that inaccurate parameters can result in a median depth error of up to 3 cm. This can be a serious problem in practical applications. In particular, the performance of the conventional RMA system for the very common wall medium of concrete is the worst. This illustrates the practical advantage of the present system 100, in which no prior parameters

are required in the process of determining in-wall structure. The present system 100 also outperforms the conventional RMA system in terms of having comparatively smaller horizontal distance errors and depth errors, as well as being less likely to exhibit rapid degradation of performance.

[75] The impact of water content in the wall medium on the imaging result was evaluated. In many tropical countries with humid climates, the water content in the wall can vary greatly and affect the performance of typical in-wall structure detection systems. This effect on imaging is twofold: i) water absorbs electromagnetic radiation in the radiofrequency spectrum ranging from 1 GHz to 1000 GHz, and ii) water causes a drastic permittivity change of a wall, both leading to the failure of conventional systems. Figs. 12A and 12B illustrate evaluation results of the present system 100 in relation to the impact of water content in the wall medium (increased from 0 grams per cubic meter (g/m^3) to 100 g/m^3) on the accuracies of estimating both horizontal distance and depth. The median horizontal distance error increases by around 0.3 cm on the average, while the median depth error increases by around 0.2 cm. The gradual increase of error indicates that, as the water content increases, more radio frequency signals are absorbed or blocked. The increase in water content does not lead to a steep rise in error, confirming the robustness of the present system 100 in adapting to permittivity variations (due to variation in water content), i.e., validating the present system 100 to be calibration-free.

[76] The impact of depth of the in-wall structure on the imaging result was also evaluated. As the UWB signals are greatly attenuated as they travel deep into walls, the depth of an in-wall element is a key limiting factor for conventional imaging and localization capabilities. Evaluation of the present system 100 was conducted in which in-wall elements 73 of different materials are buried at depths of 3 cm, 5 cm, and 10 cm respectively. The accuracies of estimating both horizontal distance and depth are as illustrated in Figs. 13A and 13B. Taking the concrete wall as an example, the median horizontal distance errors are 0.4 cm, 0.7 cm, and 1.5 cm while the depth errors are 0.3 cm, 0.5 cm, and 1.2 cm, respectively. Other walls follow the same trend but appear less sensitive to depth. Therefore, the present system 100 is experimentally verified to be capable of delivering acceptable accuracy even as the depth increases.

[77] As discussed above, conventional systems are sensitive to the moving speed of the probe (swiping speed), which presents potentially significant performance degradation. Experimental evaluation and validation demonstrate that the present system 100 is not sensitive to the probe swiping speed. In the evaluation, a user moves the probe 200 on the wall surface with substantially constant speeds of 1 cm/s, 2 cm/s, and 4 cm/s. The evaluation results as illustrated in Figs. 14A and 14B show the impact of moving speed of the probe on the median errors or accuracies of estimating both horizontal distance and depth remain almost the same, regardless of the probe swiping speed. This demonstrates that the present system 100 is robust enough for the probe to be portable or hand-held. That is, moving the probe 200 at any arbitrary speed does not adversely affect the accuracy of the present system 100. In other words, the imaging result determined according to embodiments of the method 700 is determined independently of the speed at which the probe is moved over the moving distance.

[78] To investigate the effects of different materials of in-wall elements 73, three common materials were tested: rebar, water-filled PVC pipe, and empty PVC pipe. As illustrated in Figs. 15A and 15B, shows the impact of different material of in-wall structures on the accuracies of estimating both horizontal distance and depth. For the rebar sample and the water-filled PVC pipe example, more than 75 % of the horizontal distance errors and the depth errors are smaller than 1 cm. Although empty PVC pipes may show slightly higher percentile errors, all median errors in the horizontal distance and depth are below 1 cm. This demonstrates good that the present system 100 can be used to accurately pinpoint the position of these common in-wall elements.

[79] Material determination performance of in-wall structure for the present system 100 was evaluated with four different in-wall elements: non-corroded rebar (NR), corroded rebar (CR), non-leaked PVC pipe (NP), and leaked PVC pipe (LP). Figs. 16A to 16D illustrate confusion matrices for characterizing the material determination performance under different wall mediums. The wooden wall and the drywall present smaller distortion effect on the material determination of the in-wall element in comparison to the concrete wall and the brick wall. In summary of the data collected, the overall accuracy in determining the in-wall element material (e.g., steel or PVC) is 95.2%. Diagnosis of the health/condition of the in-wall element has an accuracy of about 91.8%. These represent relatively high accuracy

in the identification of the materials and the diagnosis of the structural health.

[80] The impact of the depth of the in-wall structure on material determination of the present system 100 was evaluated. Figs. 17A and 17B show that the accuracies of material determination and status diagnosis in relation to the depth of in-wall structures, i.e. the identification of the materials slightly decreases as the depth increases. Nevertheless, the system 100 is capable of over 90% accuracy in the identification of the materials, and over 80% accuracy in the diagnosis of the condition of the in-wall element. That is, not only can the system 100 identify whether the in-wall element is made of steel or PVC, the system 100 can also diagnose the condition of the in-wall element, e.g., whether a pipe is rusted or whether there is water-ingression. The results validate the effectiveness of the present system 100 in successfully removing the influence caused by varying wall depths, enabling a material determination process that is robust to environmental influences.

[81] The impact of water content in the wall medium on material determination (identification and/or diagnosis) was also evaluated. The presence of water is expected to block and attenuate radio-frequency signals, and reduce the accuracy of the structural inspection results. In the experiments, water content was varied in the wall medium from 0 grams per cubic meter $(g/m^3)$to 100 g/m^3. Figs. 18A and 18B illustrate results of material determination and status diagnosis performance. It can be observed that the overall material determination accuracies and diagnosis accuracies remain over 90% and 80%, respectively, confirming the robustness of the present system 100.

[82] The evaluation on the effect of separating the 1-D UWB signal 430 into a co-polarization signal and a cross-polarization signal for input to the second DNN 330 was also performed. The overall material determination and diagnosis accuracies are 95.2% and 91.8% for dual polarization, and 86.1% and 70.5% for single polarization.

[83] In-wall crack detection is an important part of non-destructive structural inspection. To verify the performance of the present system 100 in this aspect, a cement layer was applied on top of the cracked concrete block 71 shown in Fig. 19A. This allows the emulation of in-wall cracks 73/72 while having full knowledge of the ground truth. The probe 200 was moved over the surface of the cement layer, along each of the three paths 88 (marked with arrows). The imaging results generated by the present system 100 are shown

in Fig. 19B. Data collected along each path 88 was used to produce a corresponding sub-figure 50 showing a 2-D "cross-sectional" image along the width x (moving dimension) and depth z. In these images 50, one may clearly discern major cracks and dents as bright or distinguishable spots/features 52. The results clearly demonstrate the ability of the present system 100 in identifying in-wall cracks.

[84] The present system 100 may also be used where the wall is multi-layered and/or formed of a multi-material wall medium. Fig. 20A is an image of an exemplary 1.5 cm thick wooden tile covering a concrete block, such as may be used for indoor aesthetic decoration. The concrete block is embedded with two rebars 4.5 cm deep and spaced 6 cm apart. Fig. 20B shows the imaging results obtained by the present system 100. Despite the presence of a wooden tile which introduced noise to the imaging results (owing to material discontinuity/non-homogeneity of the wall medium), the two rebars are clearly distinguishable in the imaging results with relatively high localization accuracy in both x and z directions. The experiment was conducted with relatively few samples of data of different wall medium materials.

[85] The experiments demonstrate that embodiments of the method 700 can determine a nature of any in-wall element 73 in the wall medium 70. Determining the nature includes at least one of the following: identifying a material composition of the in-wall element 73, diagnosing a condition of the in-wall element 73, and any combination thereof. Determining the nature of the in-wall element may include diagnosing a condition of the in-wall element 73 based on a change in material composition of the in-wall element 73 relative to a baseline composition, in which the condition of the in-wall element is determined in relation to a structural health of the wall 71. For example, if the material composition of the in-wall element 73 is determined to be corroded steel, the baseline composition may be steel, the condition of the rebar can be concurrently determined based on the change in material composition from steel to corroded steel. The overall structural health of the wall 71 may be determined by taking into account the materials and the conditions determined in respect of each of the wall medium and the one or more in-wall elements 73 embedded in the wall 71.

[86] The above describes embodiments of the present method 700 of structural

inspection. The method 700 has been demonstrated to be capable of detecting an in-wall element in a wall medium. The method 700 includes receiving a two-dimensional (2D) Ultra-Wide Band (UWB) signal matrix from a pair of cross-polarized antennas. The method 700 includes acquiring the 2-D UWB signal matrix as a first input to a first machine learning model or a first deep neural network (DNN), and obtaining an imaging result based on a first output of the first machine learning model or the first DNN. The imaging result corresponds to a position and/or depth of the in-wall element relative to a surface of the wall medium. The position and/or depth may be with reference to a starting point and/or a surface of the wall. The method 700 includes, based on the imaging result and the 2-D UWB signal matrix, extracting a one-dimensional (1-D) UWB signal sequence, and providing the 1-D UWB signal as a second input to a second machine learning model or a second DNN. The second machine learning model or the second DNN is configured to predictively determine a material of the in-wall element. The second machine learning model or the second DNN may be configured to identify the material of the in-wall element. The method 700 may be configured to diagnose a condition of the in-wall element based on a second output of the second machine learning model or a second output of the second DNN.

[87] The method 700 may further include separating the 1-D UWB signal into a co-polarization signal and a cross-polarization signal. The second input to the second machine learning model or the second DNN is configured in the form of the co-polarization signal and the cross-polarization signal. The method 700 may further include independently training the first machine learning model and the second machine learning model. That is to say, the first machine learning model and the second machine learning model are trained using different sets of training data. If the first machine learning model is trained using a first set of training data, the second machine learning model may be trained using a second set of training data that has been processed based on selected training data, in which the selected training data is selected from the first set of training data.

[88] The present system 100 has been demonstrated to show improved performance over the conventional system in the diagnosis of structural health, with more accurate localization (pinpointing of the position and/or depth) of in-wall elements as well as determination of the nature of the in-wall element (e.g., whether it is a strengthening element or an area of potential or current structural weakness). For example, the system 100 not only can

determine that the in-wall structure is a pipe made of steel, but it can further determine if the pipe has corroded. In contrast to the conventional system, the present system 100 does not require prior information/knowledge of parameters of the wall or the wall material. The present system 100 does away with the need to predetermine the parameters of the wall, and can thus be described as “calibration-free”. In other words, the present method 700 is independent of predetermined parameters of the wall. For example, the imaging result is determined independently of predetermined parameters of the wall 71 because the method 700 does not involve prior acquisition of parameters such as the permittivity of the wall medium 70, or the position and depth of any in-wall elements 73, etc. The system 100 has been demonstrated to show improved performance even when the wall medium 70 is formed of non-homogenous materials such as concrete. The system 100 has been experimentally verified to give accurate and useful results in cases where the wall medium 70 includes a plurality of materials, e.g., where the wall includes a multi-layered structure or composite materials. With the present system 100, non-homogeneity of the wall and a lack of prior information of the wall no longer hinder the user from performing sufficiently accurate structural inspection.

[89] The system 100 provides the user with the ability to inspect and diagnose the structural integrity and functional conditions of supportive elements. This enables early detection of potential issues with in-wall elements and the wall medium, e.g., where the strength of concrete and/or rebars have been compromised by environmental influences, such as erosion, corrosion, water seepage, etc. Advantageously, the present system 100 can serve as a tool for a comparatively comprehensive assessment of the structural integrity of walls.

[90] All examples described herein, whether of apparatus, methods, materials, or products, are presented for the purpose of illustration and to aid understanding, and are not intended to be limiting or exhaustive. Various changes and modifications may be made by one of ordinary skill in the art without departing from the scope of the invention as claimed.

CLAIMS

1. A method of non-destructive structural inspection of a wall, the wall including a wall medium, the method comprising:

providing a first input to a first deep neural network, the first input being a two-dimensional (2-D) Ultra-Wide Band (UWB) signal matrix acquired by a pair of cross-polarized antennas, the pair of cross-polarized antennas being disposed on a probe moved from a starting point over a moving distance across a surface of the wall;

determining an imaging result based on a first output of the first deep neural network, the imaging result being determined independently of one or more predetermined parameters of the wall;

determining a one-dimensional (1-D) UWB signal sequence based on the imaging result and the 2-D UWB signal matrix;

acquiring a second output of a second deep neural network, wherein the second deep neural network is configured to receive a second input based on the 1-D UWB signal sequence; and

responsive to the second output having one or more anomalies relative to baseline component:

determining a nature of an in-wall element corresponding to at least one of the one or more anomalies; and

determining a location of the at least one of the one or more anomalies based on the imaging result.

2. The method as recited in claim 1, wherein the one or more anomalies of the in-wall element corresponds to at least one of: an in-wall defect, an in-wall structure, and a local difference in the wall medium.

3. The method as recited in claim 1 or claim 2, further comprising: transmitting a plurality of UWB signals from a transmitter antenna toward the wall, the transmitter antenna being disposed on the probe such that the transmitter antenna is parallel to one of the pair of cross-polarized antennas and such that the transmitter antenna is perpendicular to another of the pair of cross-polarized antennas, such that the probe is operable as a monostatic probe.

4. The method as recited in any of claims 1 to 3, wherein the imaging result is determined independently of a speed at which the probe is moved over the moving distance..

5. The method as recited in any of claims 1 to 4, further comprising separating the 1-D UWB signal sequence into a co-polarization signal and a cross-polarization signal, wherein the co-polarization signal and the cross-polarization signal are configured as the second input to the second deep neural network.

6. The method as recited in claim 5, wherein the co-polarization signal and the cross-polarization signal respectively received by the pair of cross-polarized antennas are used to determine a respective polarization direction of the 1-D UWB signal.

7. The method as recited in any of claims 1 to 6, wherein determining the nature of the in-wall element comprises at least one of the following: identifying a material composition of the in-wall element, diagnosing a condition of the in-wall element, and a combination thereof.

8. The method as recited in any of claims 1 to 7, further comprising diagnosing a structural health of the wall based on at least one of the following: the nature of the at least one in-wall element, a nature of the wall medium, a change in the nature of the at least one in-wall element, a change in the nature of the wall medium, and any combination thereof.

9. The method as recited in any of claims 2 to 8, wherein the 2-D UWB signal matrix comprises a plurality of selected time series signals, wherein each of the plurality of selected time series signals is selected from a plurality of antenna time series signal received by the pair of cross-polarized antennas.

10. The method as recited in claim 9, wherein each of the plurality of time series signals corresponds to a position of the pair of cross-polarized antennas relative to the starting point and/or the moving distance.

11. The method as recited in any of claims 1 to 10, wherein the first deep neural network comprises an encoder module and a decoder module, wherein the encoder module is configured to contract the 2-D UWB signal matrix into an intermediate matrix, and wherein the decoder module is configured to upscale the intermediate matrix to determine the imaging result.

12. The method as recited in claim 11, wherein the decoder module includes a plurality of up-sampling levels in a series connection, and wherein each of the plurality of up-sampling levels is configured to receive an input from the encoder module.

13. The method as recited in any of claims 1 to 12, wherein the second deep neural network comprises a material identifier module configured to determine the material.

14. The method as recited in claim 13, wherein the second deep neural network further comprises an environmental discriminator module configured to remove an environmental influence corresponding to the wall medium.

15. The method as recited in any of claims 1 to 14, wherein the first deep neural network and the second deep neural network are trained independently of one another.

16. The method as recited in any of claims 1 to 15, wherein the second deep neural network is trained via an adversarial learning method.

17. A system for non-destructive structural inspection of a wall, the wall including a wall medium, the system comprising:

a probe movable over a moving distance across a surface of the wall, the probe including a pair of cross polarized antennas; and

a controller in signal communication with the probe, the controller being configured to perform the method as recited in any one of claims 1 to 16.

18. The system as recited in claim 17, wherein the probe is configured to be held by hand by a user to move the probe between the starting point and a terminal point to determine one or both of the following: a position of the in-wall element relative to the starting point and a depth of the in-wall element relative to the surface of the wall.

19. The system as recited in claim 18, further comprising a user interface configured to receive the first output and the second output, the user interface being configured to output at least one of the following: the position of the in-wall element, the depth of the in-wall element, a material composition of the in-wall element, a condition of the in-wall element, a structural health determination of the wall, and any combination thereof.

20. The system as recited in any of claims 17 to 19, wherein the probe is configured as a monostatic probe.