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(54) A METHOD FOR COMPUTER-AIDED ANALYSIS OF MEDICAL IMAGES

VERFAHREN ZUR RECHNERGESTÜTZTEN ANALYSE MEDIZINISCHER BILDER

PROCÉDÉ D'ANALYSE ASSISTÉE PAR ORDINATEUR D'IMAGES MÉDICALES

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Description

[0001] The invention refers to a method for computer-aided analysis of medical images as well as to a corresponding apparatus.

[0002] The invention belongs to the field of detecting calcified plaques in vessels (particularly arteries) by analysing medical images. Based on the detected calcified plaques, a physician can perform a diagnosis of a patient in order to reveal artery diseases. Particularly for cardiac medical images, the detection of calcified plaques is very important for a subsequent diagnosis of diseases and particularly for diagnosing coronary artery disease.

[0003] In most clinical tools, a semi-automatic approach is used for detecting calcified plaques in arteries. To do so, groups of voxels in 3D CT scans being potential candidates for calcified plaques are automatically identified. The identified groups of voxels are then manually assigned to specific vessels in order to distinguish the coronary calcium inside vessels from bone, calcium outside of vessels and noise.

[0004] Document [8] discloses a method for automatic detection of calcified coronary plaques in computed tomography data sets where both native and angio data sets of one person are processed.

[0005] Document [9] discloses a method for automatic machine learning scoring of computed tomography data sets, where an angio atlas is registered to a native data set of a person.

[0006] It is an object of the invention to provide a method and an apparatus for computer-aided analysis of medical images enabling an automatic detection of calcified plaques within vessels.

[0007] The computer implemented method of the invention analyses a pair of medical images, where said pair includes a first image which is a contrasted scan of a part in a human or animal body (i.e. a scan made after injecting a contrast agent in the human or animal body) and a second image which is a native scan of the same part of the human or animal body without contrast agent. The native scan is usually taken before the contrasted scan. This is because the contrast agent remains a certain time in the human and animal body, thus not enabling a native scan. Based on the inventive method, the following steps a) to e) are performed.

[0008] In a step a), one or more anatomic structures are identified within both the first image and the second image, resulting in a positional information of the one or more anatomic structures in the first and second images.

[0009] In a step b), first centerlines of vessels and particularly arteries in the first image are identified, resulting in a positional information of the first centerlines in the first image.

[0010] In a step c), second centerlines of vessels in the second image corresponding to respective first centerlines in the first image are identified, resulting in a positional information of the second centerlines in the second image. In this step c), the identification of the second centerlines comprises the step of mapping the first centerlines from the first image to the second image by estimating a spatial transform from the first image to the second image based on the identified one or more anatomic structures in the first and second images.

[0011] Thereafter, candidate calcified plaques are extracted in the second image in a step d) and calcified plaques out of the candidate calcified plaques are identified by a machine learning classifier (i.e. a classifier learned by a computer-implemented machine learning method). This machine learning classifier processes a number of features of the candidate calcified plaques. The above mentioned step d) and/or step e) uses the positional information of the second centerlines in the second image which has been determined in step c).

[0012] The invention is based on the finding that vessels can be extracted more accurately in contrasted scans than in native scans. However, calcified plaques can be found easier in native scans. By processing both scans and using the positional information of identified centerlines of vessels, a fast, accurate and automatic computer-implemented detection of calcified plaques belonging to vessels can be achieved.

[0013] In a particularly preferred embodiment, the medical images processed by the method of the invention are three-dimensional scans and/or CT scans (CT = computer tomography). Particularly, three-dimensional CT scans are processed by the method of the invention. However, the method may also be used for MRT scans and particularly 3D MRT scans (MRT = Magnetic Resonance Tomography).

[0014] The detection of calcified plaques is particularly important in coronary arteries. Hence, in a preferred embodiment, the medical images are scans of a human or animal heart wherein the identified first and second centerlines of vessels refer to coronary arteries.

[0015] When analysing medical images of a human or animal heart, the one or more anatomic structures identified in step a) preferably comprise the pericardium and/or the aortic root in the human or animal heart.

[0016] For identifying the anatomic structures, well-known prior art methods can be used. In a particularly preferred embodiment, marginal space learning is used for this identification. Known prior art methods may also be used for the estimation of the spatial transform in step c). In a particularly preferred embodiment, the estimation of the spatial transform is based on the well-known thin-plate-spline model which takes into account the deformation of the anatomic structures in both images. However, other models can also be used for the spatial transform, e.g. an affine transform model.

[0017] In another embodiment of step d) of the invention, respective extracted candidate calcified plaques are each assigned to a specific vessel which is the vessel having a second centerline to which most of the image elements of the respective extracted candidate calcified plaque has the smallest distance. Here and in the following, the term "distance of an image element to a centerline" refers to the length of the shortest straight line between the image element and the centerline. In the case of 3D scans, an image element refers to a voxel, whereas an image element is a pixel in case of a 2D scan.

[0018] In another preferred embodiment of step d), candidate calcified plaques are also extracted from the first image, where the spatial transform in step c) is refined based on the positional differences between corresponding candidate calcified plaques in the first and the second images and where the method is continued based on the positional information of the second centerlines derived from the refined spatial transform. This embodiment enables a more accurate detection of calcified plaques.

[0019] In a particularly preferred embodiment, the above defined refinement of the spatial transform in step c) is such that the mean minimum distance between corresponding candidate calcified plaques in the first and the second images is minimized. The minimum distance is the smallest possible distance between an image element in the candidate calcified plaque of the first image and an image element in the candidate calcified plaque of the second image.

[0020] In a particularly preferred embodiment, the extraction of the candidate calcified plaques from the first image is only performed if a first condition is fulfilled, where the first condition is preferably such that a number of extracted candidate calcified plaques in the second image exceeds a predetermined first threshold (e.g. 3).

[0021] In another preferred embodiment, the refinement of the spatial transform is only performed if a second condition is fulfilled, where the second condition is preferably such that the number of extracted candidate calcified plaques in the first image exceeds a predetermined second threshold (e.g. 3) .

[0022] In a particularly preferred variant of the invention, the machine learning classifier is a random forest classifier. Alternatively, other machine learning classifiers may be used, e.g. a support vector machine, a linear discriminant analysis, a logistic regression or a probabilistic boosting tree.

[0023] In another preferred embodiment of the invention, the candidate calcified plaque extraction of step d) identifies as candidate calcified plaques in the second image groups of adjacent image elements in which each image element has a radiodensity exceeding a predetermined value. The radiodensity is a well-known quantity detected for image elements in medical images. It is usually measured in Hounsfield units abbreviated as HU.

[0024] In order to reduce the number of false positive candidate calcified plaques in the second image, the identification of the groups of adjacent image elements is a provisional identification which is discarded if at least one condition out of a number of conditions is fulfilled, where the number of conditions comprises one or more of the following conditions:

- all image elements in the group of adjacent image elements are outside a predefined anatomic structure in the second image, particularly outside the pericardium;
- the number of image elements in the group of adjacent image elements is less than a predetermined value (e.g. 3) ;
- the mean distance of the image elements in the group of adjacent image elements to the second centerlines is higher than a predetermined threshold (e.g. 15 mm);
- all image elements in the group of adjacent image elements is inside a predefined anatomic structure in the second image, particularly inside the aortic root;
- the maximum radiodensity of the image elements in the group of adjacent image elements in the second image is less than a predetermined value (e.g. 140 HU);
- the mean radiodensity difference between the image elements in the group of adjacent image elements and the image elements in a predefined neighborhood around the group of adjacent image elements is higher than a predetermined threshold (e.g. 90 HU).

[0025] The above mentioned predefined neighborhood is preferably defined such that this neighborhood comprises a predefined number of adjacent pixels around the group of adjacent image elements.

[0026] In case that the extraction step d) uses the positional information of the second centerlines, the above defined mean distance to the second centerlines is used as the positional information in a preferred variant of the invention.

[0027] In another preferred embodiment of the invention, the number of features processed in step e) comprises one or more of the following features and particularly all of the following features:

- the number of image elements in the respective candidate calcified plaque;
- the mean radiodensity of the image elements in the respective candidate calcified plaque;
- the maximum radiodensity of the image elements in the respective candidate calcified plaque;
- the number of image elements in the respective candidate calcified plaque above one or more threshold radiodensity values;
- the number of image elements in the respective candidate calcified plaque above one or more threshold radiodensity values normalized by the number of image elements in the respective candidate calcified plaque;
- the mean radiodensity of the image elements in a predefined neighborhood around the respective candidate calcified

plaque;

- the maximum radiodensity of the image elements in a predefined neighborhood around the respective candidate calcified plaque;
- the radiodensity standard deviation of the image elements in a predefined neighborhood around the respective candidate calcified plaque;
- the difference between the mean radiodensity of the image elements in the respective candidate calcified plaque and the mean radiodensity of the image elements in a predefined neighborhood around the respective candidate calcified plaque;
- the difference between a first value and a second value, the first value being the difference between the mean radiodensity of the image elements in the respective candidate calcified plaque and the mean radiodensity of the image elements in a predefined neighborhood around the respective candidate calcified plaque and the second value being the radiodensity standard deviation of the image elements in a predefined neighborhood around the respective candidate calcified plaque;
- one or more statistical values referring to the distances of respective image elements in the respective candidate calcified plaque to the closest point of the second centerlines in the second image, the closest point being the point closest to the respective image element;
- the center of gravity of the respective candidate calcified plaque in on or more coordinate systems.

[0028] As mentioned before, the predefined neighborhood preferably refers to a predefined number of adjacent pixels around the respective candidate calcified plaque. In case that step e) uses the positional information of the second centerlines, one or more of the above features processing second centerlines are used in a preferred embodiment of the invention. Important features are also the above defined difference between the mean radiodensity of the image elements in the respective candidate calcified plaque and the mean radiodensity of the image elements in a predefined neighborhood as well as the above difference between the first value and the second value.

[0029] In a particularly preferred variant of the invention, the one or more statistical values referring to the distances of image elements in the respective candidate calcified plaque to the closest point of the second centerlines in the second image comprise one or more of the following values:

- the mean of the distances;
- the standard deviation of the distances;
- the maximum of the distances;
- the median of the distances;
- the mean absolute deviation of the distances from the median of the distances.

[0030] Besides the above method, the invention also refers to an apparatus for computer-aided analysis of medical images, where a pair of medical images is analysed, the pair including a first image which is a contrasted scan of a part of a human or animal body and a second image which is a native scan of the same part of a human or animal body. This apparatus comprises a computer comprising program code performing.

- a step a) which is a step of identifying one or more anatomic structures within both the first image and the second image, resulting in a positional information of the one or more anatomic structure in the first and second images;
- a step b) which is a step of identifying first centerlines of vessels in the first image, resulting in a positional information of the first centerlines in the first image;
- a step c) which is a step of identifying second centerlines of vessels in the second image corresponding to respective first centerlines in the first image, resulting in a positional information of the second centerlines in the second image, where the identification of the second centerlines comprises the step of mapping the first centerlines from the first image to the second image by estimating a spatial transform from the first image to the second image based on the identified one or more anatomic structures in the first and second images;
- a step d) which is a step of extracting candidate calcified plaques in the second image;
- a step e) which is a step of identifying calcified plaques out of the candidate calcified plaques by a machine learning classifier processing a number of features of the candidate calcified plaques;

wherein step d) and/or step e) is configured to use the positional information of the second centerlines in the second image.

[0031] The above apparatus of the invention is preferably configured to perform one or more preferred variants of the method of the invention.

[0032] The invention also refers to a computer program product directly loadable into the internal memory of a digital computer, comprising a program code performing the method of the invention or one or more preferred embodiments of the method of the invention, when the program code is run on a computer.

[0033] Moreover, the invention comprises a computer program including a program code for performing the method of the invention or one or more preferred embodiment of the method of the invention, when the program code is run on a computer.

[0034] Embodiments of the invention will now be described with respect to accompanying drawings wherein

Fig. 1 is a schematic view of a native CT scan of a human heart processed in an embodiment of the invention; and

Fig. 2 is a flow chart illustrating the essential steps performed in an embodiment of the invention.

[0035] In the following, the invention will be described based on medical images in the form of 3D scans of a human heart. It is the aim of the invention to identify calcified plaques in coronary vessels in the human heart based on both a native (non-contrasted) CT scan and a contrasted CT scan. The contrasted CT scan corresponds to an embodiment of a first image and the native CT scan corresponds to an embodiment of a second image as defined in the patent claims.

[0036] Fig. 1 is a schematic illustration of a two-dimensional slice of a native 3D CT scan processed in the embodiment described herein. The native CT scan is referenced as image I2. The hatched structure in Fig. 1 illustrates the structure of a human heart. In the real visualization, this structure is an area of different gray levels which may also include white partitions. Furthermore, the background of the image I2 is substantially black in the real visualization. The corresponding contrasted CT scan named as image I1 in Fig. 2 is not shown separately but it has a similar structure as the scan of Fig. 1. However, the contrast is better making it easier to identify separate areas of the human heart as well as coronary arteries due to the use of a contrast agent.

[0037] The invention as described in the following is implemented as software in a computer and analyses both the contrasted and native CT scans I1 and I2 in order to identify calcified plaques in coronary arteries and to distinguish those calcified plaques from calcifications of bones which may also be included in the CT scans. Contrary to the prior art, an automatic approach for identifying calcified plaques without human interaction is provided.

[0038] In the first step of this approach, an anatomic information in the form of anatomic structures is extracted from both the contrasted and the native scans I1, I2 which form the input of the method. This is indicated as step S1 in Fig. 2. In the embodiment described herein, a segmentation of the pericardium forming an anatomic structure in the sense of the patent claims is detected as the boundary AS1 (dashed line) in the native CT scan I1 of Fig. 1. Analogously, the aortic root which is also an anatomic structure in the sense of the patent claims is identified as boundary AS2 (dashed line) in the native CT scan I2 of Fig. 1. In the same way as in Fig. 1, corresponding anatomic structures in the form of the pericardium and the aortic root are identified in the contrasted CT scan I1. The segmentation of the pericardium and the aortic root is performed by a well-known prior art method. In the embodiment described herein, so-called marginal space learning (MSL) as introduced in document [1] is used for segmentation. MSL is used to estimate the position, orientation and size of the heart. A mean shape (which is trained on a set of example shapes) is then aligned with the estimated pose as an initial estimate of the boundary of the pericardium and the aortic root. In the MSL method performed in this embodiment, learning-based boundary detectors are used to guide the boundary evolution under the well-known active shape model (ASM) framework. However, the sternum and ribs are often included in the automatically segmented pericardium mesh when applying ASM directly. To distinguish sternum and ribs from the pericardium and aortic root, a post-processing step is performed in order to explicitly segment these bones to avoid the interference with the calcium scoring for calcified plaques. In the embodiment described herein, the post-processing step as disclosed in document [2] was implemented in the analysing method.

[0039] In a next step named as S2 in Fig. 2, centerlines for the coronary artery tree are automatically extracted from the contrasted CT scan using the method as described in document [3]. A learning based verification step as described in document [4] corrects for vessel tree parts erroneously traced into non-vessel structures. As a result of step S2, coronary centerlines forming the coronary centerline tree are identified in the contrasted CT scan I1. Those coronary centerlines are named as CL1 in Fig. 2.

[0040] In the next step S3 of Fig. 2, the coronary centerlines CL1 are mapped from the contrasted scan I1 to the native scan I2 based on the segmented pericardium meshes and the overlapping parts of the aortic root (starting from the hinges). In other words, a spatial transform from the contrasted CT scan to the native CT scan is estimated in order to identify the coronary centerlines as extracted in the contrasted scan in the corresponding native scan. Point correspondences between the segmentation meshes of the native and the contrasted scan can be assumed since a model-based approach (ASM) has been used. In the embodiment described herein, the well-known thin-plate-spline (TPS) model as described in document [5] is used for estimating the spatial transform. This model interpolates the deformation field within the pericardium. However, other point-based registration (mapping) methods (rigid as well as deformable) could be applied. Nevertheless, the TPS model has the advantages that the interpolation is smooth with derivatives of any order and that the model has no free parameters that need manual tuning and that it has closed-form solutions for both warping and parameter estimation.

[0041] As a result of the mapping step S3, centerlines CL2 of coronary arteries are identified in the native CT scan.

Those centerlines CL2 are illustrated as solid lines in the native CT scan as shown in Fig. 1. The identified centerlines refer to different arteries in the human heart, namely the left anterior descending LAD, the first diagonal D1 and the left circumflex LCX. The assignment of those arteries to the centerlines are indicated in Fig. 1 by corresponding reference numerals in brackets.

[0042] In the next step S4, candidate calcified plaques CCP are extracted in the native scan I2. To do so, the radiodensities (also named as intensities in the following) in Hounsfield units (HU) of three-dimensional voxels in the 3D native scan are processed. Particularly, connected groups of voxels (3D 6-connectivity), i.e. voxels having at least one common boundary point, with intensities above t_{cal} = 130 HU are identified as possible candidate calcified plaques. However, additional constrains are imposed taking into account the centerlines CL2 in the native CT scan. This was done in order to reduce the number of (false positive) candidates. In other words, a possible CCP is discarded as a CCP if at least one of the following conditions is fulfilled:

1. All voxels of a respective connected group are outside the pericardium.
2. The number of voxels in the respective connected group is less than n = 3.
3. The mean distance of the voxels in the respective connected group to the coronaries (i.e. to the centerlines CL2) is more that d_v = 15 mm.
4. All voxels in the respective connected group are within the aortic root.
5. The maximum intensity of the voxels in the respective connected group is less than I_{max} = 140 HU.
6. The mean intensity difference to the surrounding tissue of the respective connected group is less than D_{max} = 90 HU.

[0043] Here and in the following, the term "distance of a voxel to a coronary/centerline" refers to the length of the shortest straight line between the voxel and the coronary/centerline. The intensity of the surrounding tissue is computed as the mean intensities of 100 voxels around the possible calcified plaque CCP. Finally, the extracted CCPs are labeled as belonging to the type of vessel to which most of its voxels are closest.

[0044] In a modification of the extraction step described above, the CCPs are also extracted from the contrasted scan if the number of CCPs extracted from the native scan in step S4 exceeds a certain number (e.g. N_{CCP} = 3). To do so, different from the native scan, the intensity threshold t_{cal} for calcification needs to be adjusted to the lumen intensity in the contrasted scan which is close to that of calcium due to the injected contract agent. To this end, the mean μ_{lum} and standard deviation σ_{lum} of the lumen intensity are estimated from voxels within the segmented ascending aorta, where a small border to the aortic wall is kept to exclude potential calcifications. Based on these, a calcification threshold of $t_{cal} = \mu_{lum} + 1.2\ \sigma_{lum}$ is used for CCP extraction. Furthermore, of the six constraints listed above, only the first three are applied to CCPs from the contrasted scans. However, the third constraint is modified in that the mean distance to the closest calcified centerline point should not exceed d_v = 10 mm, where calcified centerline points are identified by the calcification detector as described in document [6].

[0045] If the number of CCPs extracted from the contrasted scan again exceeds N_{CCP}, the registration (mapping) between the contrasted and native scan is refined. To do so, the translational part of the spatial transform estimated in step S3 is adjusted as to minimize the mean minimum distance between the CCPs of the native and the contrasted scans. The refined spatial transform leads to new positions of centerlines CL2. Based on these new positions, the extraction of calcified plaques is repeated in step S4, resulting in new CCPs which are then labeled as belonging to the type of vessel to which most of its voxels are closest, as it is the case in the previously described variant of the method.

[0046] In a next step S5, a machine learning classifier trained by corresponding training data was used in order to distinguish between true positive and false positive CCPs as extracted in step S4. In the embodiment described herein, the so-called random forest classifier RFC (see document [7]) was applied. The random forest classifier is an ensemble learning method that operates by constructing a multitude of decision trees at training time and outputting the class based on the rate of the classifications of all individual decision trees (particularly based on the majority vote). During training, a predetermined number of observations in the training data are sampled, with replacement. Furthermore, a number of randomly selected features of the observations are used at each node (i.e. at each split in the decision trees) when learning the individual tree. As the random forest classifier is well-known in the prior art, a detailed description of this classifier is omitted.

[0047] In the embodiment described herein, a total of 36 features as listed in the following Table 1 are used for training and applying the random forest classifier. The classifier was tested with different probability thresholds. In case that the rate of the classifications of all individual decision trees in the class "calcified plaque" (out of the classes "calcified plaque" and "not being a calcified plaque") exceeds the predetermined threshold, the candidate calcified plaque is regarded as a calcified plaque. The results presented in the following are based on a probability threshold of 0.5.

Table 1:

name	parameter range	description
size	-	number of voxels
meangray	-	mean intensity
maxgray	-	maximum intensity
ccnt<n>	<n> = 134:4:166	number of voxels above <n> Hounsfield units
chist<n>	<n> = 134:4:166	ccnt<n> normalized by the number of voxels
Imeangray	-	mean intensity of voxels in local neighborhood
Imaxgray	-	maximum intensity of voxels in local neighborhood
Istdgray	-	intensity standard deviation in local neighborhood
Idgray	-	meangray - Imeangray
Iddgray	-	Idgray - Istdgray
vdist _<t>	<t> ∈ {mean, std, max, median, mad}	statistics of the voxel distances to the closest centerline point
cog_<t>	$\langle t \rangle \in \{x, y, z\}$	center of gravity relative to the pericardium
cog_<t>	$\langle t \rangle \in \{\sin, \cos\}$	center of gravity in cylindrical coordinates

[0048] In the above table, the features refer to the voxels within a corresponding extracted CCP. The term "local neighborhood" in the table refers to a predefined number of adjacent voxels (e.g. 100 voxels) around the candidate calcified plaque. Moreover, the expression <n> = 134:4:166 in the above table indicates that, as thresholds for the Hounsfield units, numbers of voxels between 134 and 166, subsequently being incremented by four, are used. Furthermore, the following abbreviations apply in the above table:

mean = the mean of the voxel distances;

std = standard deviation of the voxel distances;

max = maximum of the voxel distances;

median = the median of the voxel distances;

mad = median absolute deviation of the voxel distances from the median of the distances.

[0049] Summarized, for each candidate calcified plaque, the above features of Table 1 are input in the random forest classifier which outputs as a result whether the candidate classified plaque can be identified as a calcified plaque CP within a vessel or not. The calcified plaques CP identified by the random forest classifier RFC in step S5 are eventually output by the analysing method, as indicated in Fig. 2.

[0050] The above described analysing method was tested based on native and contrasted scans for 64 patients. These were equally divided into a training (32) and a testing (32) set, each of which contains respectively 8 patients acquired on CT scanners from four different vendors. For the training set, also ground truth annotations (i.e. the correct classification as calcified plaque or not) were provided. The random forest classifier has been trained in a leave-one-patient-out (LOPO) fashion. For evaluation, the well-known sensitivity SENS and the positive predictive value PPV have been computed on a voxel-wise basis as well as on a lesion-wise basis. Using the voxel-wise basis, the correct classification of each voxel is checked. When using the lesion-wise basis, the correct classification of extracted candidate calcified plaques as a whole is checked. Moreover, the well-known interclass correlation coefficient ICC for the Agatston score is computed on the ground true and the automatic detections respectively. The Agatston score is a well-known quantity describing the degree of coronary calcification. Furthermore, the number of true positives TP, false negatives FN and false positives FP has been calculated for the lesion-wise evaluation. The method performs the better, the closer the respective values SENS, PPV and ICC are to 100 % or 1.0. The results for the tested method are shown in the following Table 2.

Table 2:

voxel-wise		lesion-wise			Agatston ICC
SENS	PPV	SENS	PPV	TP/FN/FP	
96.12%	90.71%	85.33%	91.28%	157/27/15	0. 968

[0051] Evidently, all values are close to the optimum value of 100 % or 1.0. Hence, the analysis method of the invention provides a very accurate detection of calcified plaques in coronary vessels.

[0052] The invention as described in the foregoing has a number of advantages. Particularly, the invention provides a fully automatic detection for coronary vessels which does not need human interactions. By using the coronary vessel tree estimated from a contrasted scan, the individual vessels can be localized much more accurately in the native scan than by using a general, patient-independent prior. Furthermore, calcifications identified in both scans can be optionally used to further improve this accuracy. The mapping of the contrasted and native scans based on segmented anatomic structures is very fast in comparison to image-based registration. Due to the fully automatic approach, the physician can safe time for analysing CT scans.

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Claims

1. A computer implemented method for computer-aided analysis of medical images, where a pair of medical images is analysed, the pair including a first image (I1) which is a contrasted scan of a part in a human or animal body and a second image (I2) which is a native scan of the same part of the human or animal body without contrast agent,

the method comprising the steps of:

a) identifying one or more anatomic structures (AS1, AS2) within both the first image (I1) and the second image (I2), resulting in a positional information of the one or more anatomic structures (AS1, AS2) in the first and second images (I1, I2);
b) identifying first centerlines (CL1) of vessels in the first image (I1), resulting in a positional information of the first centerlines (CL1) in the first image (I1);
c) identifying second centerlines (CL2) of vessels in the second image (I2) corresponding to respective first centerlines (CL1) in the first image (I1), resulting in a positional information of the second centerlines (CL2) in the second image (I2), where the identification of the second centerlines (CL2) comprises the step of mapping the first centerlines (CL1) from the first image (I1) to the second image (I2) by estimating a spatial transform from the first image (I1) to the second image (I2) based on the identified one or more anatomic structures (AS1, AS2) in the first and second images (I1, I2);
d) extracting candidate calcified plaques (CCP) in the second image (I2);
e) identifying calcified plaques (CP) out of the candidate calcified plaques (CCP) by a machine learning classifier (RFC) processing a number of features of the candidate calcified plaques (CCP);

wherein step d) and/or step e) uses the positional information of the second centerlines (CL2) in the second image (I2).

2. The method according to claim 1, wherein the medical images (I1, I2) are three-dimensional scans and/or CT scans, particularly three-dimensional CT scans.

3. The method according to claim 1 or 2, wherein the medical images (I1, I2) are scans of a human or animal heart wherein the identified first and second centerlines (CL1, CL2) of vessels refer to coronary arteries.

4. The method according to claim 3, wherein the identified one or more anatomic structures (AS1, AS2) comprise the pericardium and/or the aortic root in the human or animal heart.

5. The method according to one of the preceding claims, wherein marginal space learning is used in step a) for identifying the one or more anatomic structures (AS1, AS2) in the first and second images (I1, I2).

6. The method according to one of the preceding claims, wherein the estimation of the spatial transform in step c) is based on the thin-plate-spline model or an affine transform model.

7. The method according to one of the preceding claims, wherein in step d) respective extracted candidate calcified plaques (CCP) are each assigned to a specific vessel which is the vessel having a second centerline (CL2) to which most of the image elements of the respective extracted candidate calcified plaque (CCP) have the smallest distance.

8. The method according to one of the preceding claims, wherein in step d) candidate calcified plaques (CCP) are also extracted from the first image (I1), where the spatial transform in step c) is refined based on the positional differences between corresponding candidate calcified plaques (CCP) in the first and the second images (I1, I2) and where the method is continued based on the positional information of the second centerlines (CL2) derived from the refined spatial transform.

9. The method according to claim 8, wherein the refinement of the spatial transform in step c) is such that the mean minimum distance between corresponding candidate calcified plaques (CCP) in the first and the second images (I1, I2) is minimized.

10. The method according to claim 8 or 9, wherein the extraction of the candidate calcified plaques (CCP) from the first image (I1) is only performed if a first condition is fulfilled, where the first condition is preferably such that the number of extracted candidate calcified plaques (CCP) in the second image (I2) exceeds a predetermined first threshold.

11. The method according to one of claims 8 to 10, wherein the refinement of the spatial transform is only performed if a second condition is fulfilled, where the second condition is preferably such that the number of extracted candidate calcified plaques (CCP) in the first image (I1) exceeds a predetermined second threshold.

12. The method according to one of the preceding claims, wherein the machine learning classifier (RFC) is a random forest classifier or a support vector machine or a linear discriminant analysis or a logistic regression or a probabilistic

boosting tree.

13. The method according to one of the preceding claims, wherein the candidate calcified plaque extraction of step d) identifies as candidate calcified plaques (CCP) in the second image (I2) groups of adjacent image elements in which each image element has a radiodensity exceeding a predetermined value.

14. The method according to claim 13, wherein the identification of the groups of adjacent image elements is a provisional identification which is discarded if at least one condition out of a number of conditions is fulfilled, where the number of conditions comprises one or more of the following conditions:

- all image elements in the group of adjacent image elements are outside a predefined anatomic structure (AS1) in the second image (I2);
- the number of image elements in the group of adjacent image elements is less than a predetermined value;
- the mean distance of the image elements in the group of adjacent image elements to the second centerlines (CL2) is higher than a predetermined threshold;
- all image elements in the group of adjacent image elements is inside a predefined anatomic structure (AS2) in the second image (I2);
- the maximum radiodensity of the image elements in the group of adjacent image elements is less than a predetermined value;
- the mean radiodensity difference between the image elements in the group of adjacent image elements and the image elements in a predefined neighborhood around the group of adjacent image elements is higher than a predetermined threshold.

15. The method according to one of the preceding claims, wherein the number of features processed in step e) comprises one of more of the following features:

- the number of image elements in the respective candidate calcified plaque (CCP);
- the mean radiodensity of the image elements in the respective candidate calcified plaque (CCP);
- the maximum radiodensity of the image elements in the respective candidate calcified plaque (CCP);
- the number of image elements in the respective candidate calcified plaque (CCP) above one or more threshold radiodensity values;
- the number of image elements in the respective candidate calcified plaque (CCP) above one or more threshold radiodensity values normalized by the number of image elements in the respective candidate calcified plaque (CCP);
- the mean radiodensity of the image elements in a predefined neighborhood around the respective candidate calcified plaque (CCP);
- the maximum radiodensity of the image elements in a predefined neighborhood around the respective candidate calcified plaque (CCP);
- the radiodensity standard deviation of the image elements in a predefined neighborhood around the respective candidate calcified plaque (CCP);
- the difference between the mean radiodensity of the image elements in the respective candidate calcified plaque (CCP) and the mean radiodensity of the image elements in a predefined neighborhood around the respective candidate calcified plaque (CCP);
- the difference between a first value and a second value, the first value being the difference between the mean radiodensity of the image elements in the respective candidate calcified plaque (CCP) and the mean radiodensity of the image elements in a predefined neighborhood around the respective candidate calcified plaque (CCP) and the second value being the radiodensity standard deviation of the image elements in a predefined neighborhood around the respective candidate calcified plaque (CCP);
- one or more statistical values referring to the distances of respective image elements in the respective candidate calcified plaque (CCP) to the closest point of the second centerlines (CL2) in the second image (I2), the closest point being the point closest to the respective image element;
- the center of gravity of the respective candidate calcified plaque (CCP) in on or more coordinate systems.

16. The method according to claim 15, wherein the one or more statistical values referring to the distances of image elements in the respective candidate calcified plaque (CCP) to the closest point of the second centerlines (CL2) in the second image (I2) comprise one or more of the following values:

- the mean of the distances;

- the standard deviation of the distances;
- the maximum of the distances;
- the median of the distances;
- the median absolute deviation of the distances from the median of the distances.

17. An apparatus for computer-aided analysis of medical images, where a pair of medical images is analysed, the pair including a first image (I1) which is a contrasted scan of a part in a human or animal body and a second image (I2) which is a native scan of the same part of the human or animal body without contrast agent, the apparatus comprises a computer comprising program code configured to perform:

- a step a) which is a step of identifying one or more anatomic structures (AS1, AS2) within both the first image (I1) and the second image (I2), resulting in a positional information of the one or more anatomic structure (AS1, AS2) in the first and second images (I1, I2);
- a step b) which is a step of identifying first centerlines (CL1) of vessels in the first image (I1), resulting in a positional information of the first centerlines (CL1) in the first image (I1);
- a step c) which is a step of identifying second centerlines (CL2) of vessels in the second image (I2) corresponding to respective first centerlines (CL1) in the first image (I1), resulting in a positional information of the second centerlines (CL2) in the second image (I2), where the identification of the second centerlines (CL2) comprises the step of mapping the first centerlines (CL1) from the first image (I1) to the second image (I2) by estimating a spatial transform from the first image (I1) to the second image (I2) based on the identified one or more anatomic structures (AS1, AS2) in the first and second images (I1, I2);
- astep d) which is a step of extracting candidate calcified plaques (CCP) in the second image (I2);
- a step e) which is a step of identifying calcified plaques (CP) out of the candidate calcified plaques (CCP) by a machine learning classifier (RFC) processing a number of features of the candidate calcified plaques (CCP);

wherein step d) and/or step e) is configured to use the positional information of the second centerlines (CL2) in the second image (I2).

18. The apparatus according to claim 17, wherein the apparatus is configured to perform a method according to one of claims 2 to 16.

19. A computer program product directly loadable into the internal memory of a digital computer, comprising a program code for performing a method according to one of claims 1 to 16, when the program code is run on a computer.

20. A computer program comprising a program code for performing a method according to one of claims 1 to 16, when the program code is run on a computer.

Patentansprüche

1. Rechnerimplementiertes Verfahren zur rechnergestützten Analyse von medizinischen Bildern, wobei ein Paar medizinischer Bilder analysiert wird, wobei das Paar ein erstes Bild (I1) aufweist, das ein kontrastierter Scan eines Teils in einem Körper eines Menschen oder Tiers ist, und ein zweites Bild (I2), das ein nativer Scan des gleichen Teils des Körpers eines Menschen oder Tiers ohne Kontrastmittel ist, wobei das Verfahren die Schritte umfasst:

a) Identifizieren von einer oder mehreren anatomischen Strukturen (AS1, AS2) sowohl in dem ersten Bild (I1) als auch in dem zweiten Bild (I2), ergebend eine Positionsinformation der einen oder mehreren anatomischen Strukturen (AS1, AS2) in den ersten und zweiten Bildern (I1, I2);
b) Identifizieren erster Mittellinien (CL1) von Gefäßen in dem ersten Bild (I1), ergebend eine Positionsinformation der ersten Mittellinien (CL1) in dem ersten Bild (I1);
c) Identifizieren zweiter Mittellinien (CL2) von Gefäßen in dem zweiten Bild (I2), entsprechend jeweiligen ersten Mittellinien (CL1) in dem ersten Bild (I1), ergebend eine Positionsinformation der zweiten Mittellinien (CL2) in dem zweiten Bild (I2), wobei die Identifizierung der zweiten Mittellinien (CL2) den Schritt der Abbildung der ersten Mittellinien (CL1) von dem ersten Bild (I1) auf das zweite Bild (I2) mittels Schätzens einer räumlichen Transformation von dem ersten Bild (I1) zu dem zweiten Bild (I2) umfasst, basierend auf der einen oder den mehreren identifizierten anatomischen Strukturen (AS1, AS2) in den ersten und zweiten Bildern (I1, I2);
d) Extrahieren verkalkter Kandidaten-Plaques (CCP) in dem zweiten Bild (I2);
e) Identifizieren verkalkter Plaques (CP) aus den verkalkten Kandidaten-Plaques (CCP) durch einen maschi-

nellen Lernklassifikator (RFC), der eine Anzahl von Merkmalen der verkalkten Kandidaten-Plaques (CCP) verarbeitet;

wobei Schritt d) und/oder Schritt e) die Positionsinformation der zweiten Mittellinien (CL2) in dem zweiten Bild (I2) verwenden.

2. Verfahren nach Anspruch 1, wobei die medizinischen Bilder (I1, I2) dreidimensionale Scans und/oder CT-Scans, insbesondere dreidimensionale CT-Scans, sind.

3. Verfahren nach Anspruch 1 oder 2, wobei die medizinischen Bilder (I1, I2) Scans eines menschlichen oder tierischen Herzens sind, wobei sich die identifizierten ersten und zweiten Mittellinien (CL1, CL2) von Gefäßen auf Koronararterien beziehen.

4. Verfahren nach Anspruch 3, wobei die eine oder mehreren identifizierten anatomischen Strukturen (AS1, AS2) das Pericardium und/oder die Aortenwurzel in dem menschlichen oder tierischen Herzen umfassen.

5. Verfahren nach einem der vorstehenden Ansprüche, wobei in Schritt a) zum Identifizieren der einen oder mehreren anatomischen Strukturen (AS1, AS2) in den ersten und zweiten Bildern (I1, I2) "Marginal Space Learning" verwendet wird.

6. Verfahren nach einem der vorstehenden Ansprüche, wobei die Schätzung der räumlichen Transformation in Schritt c) auf dem "Thin-Plate-Spline"-Modell oder einem affinen Transformationsmodell basiert.

7. Verfahren nach einem der vorstehenden Ansprüche, wobei in Schritt d) entsprechende extrahierte verkalkte Kandidaten-Plaques (CCP) jeweils einem spezifischen Gefäß zugeordnet werden, das das Gefäß ist, das eine zweite Mittellinie (CL2) aufweist, zu der die meisten der Bildelemente der entsprechenden verkalkten Kandidaten-Plaques (CCP) den kleinsten Abstand aufweisen.

8. Verfahren nach einem der vorstehenden Ansprüche, wobei in Schritt d) verkalkte Kandidaten-Plaques (CCP) auch aus dem ersten Bild (I1) extrahiert werden, wobei die räumliche Transformation in Schritt c) basierend auf den Positionsdifferenzen zwischen entsprechenden verkalkten Kandidaten-Plaques (CCP) in den ersten und zweiten Bildern (I1, I2) entwickelt wird und wobei das Verfahren basierend auf der Positionsinformation der aus der weiterentwickelten räumlichen Transformation abgeleiteten zweiten Mittellinien (CL2) fortgeführt wird.

9. Verfahren nach Anspruch 8, wobei die Weiterentwicklung der räumlichen Transformation in Schritt c) so erfolgt, dass der mittlere Mindestabstand zwischen entsprechenden verkalkten Kandidaten-Plaques (CCP) in den ersten und zweiten Bildern (I1, I2) minimiert ist.

10. Verfahren nach Anspruch 8 oder 9, wobei die Extraktion der verkalkten Kandidaten-Plaques (CCP) aus dem ersten Bild (I1) nur durchgeführt wird, falls eine erste Bedingung erfüllt ist, wobei die erste Bedingung vorzugsweise lautet, dass die Anzahl extrahierter verkalkter Kandidaten-Plaques (CCP) in dem zweiten Bild (I2) einen vorbestimmten ersten Schwellenwert überschreitet.

11. Verfahren nach einem der Ansprüche 8 bis 10, wobei die Weiterentwicklung der räumlichen Transformation nur durchgeführt wird, falls eine zweite Bedingung erfüllt ist, wobei die zweite Bedingung vorzugsweise lautet, dass die Anzahl extrahierter verkalkter Kandidaten-Plaques (CCP) in dem ersten Bild (I1) einen vorbestimmten zweiten Schwellenwert überschreitet.

12. Verfahren nach einem der vorstehenden Ansprüche, wobei der maschinelle Lernklassifikator (RFC) ein "Random-Forest"-Klassifikator oder eine "Support-Vector-Machine" oder eine lineare Diskriminanzanalyse oder eine logistische Regression oder ein "Probabilistic Boosting Tree" ist.

13. Verfahren nach einem der vorstehenden Ansprüche, wobei die Extraktion verkalkter Kandidaten-Plaques aus Schritt d) Gruppen benachbarter Bildelemente in dem zweiten Bild (I2) als verkalkte Kandidaten-Plaques (CCP) identifiziert, in denen jedes Bildelement eine Röntgenopazität aufweist, die einen vorbestimmten Wert überschreitet.

14. Verfahren nach Anspruch 13, wobei die Identifizierung der Gruppen benachbarter Bildelemente eine vorläufige Identifizierung ist, die verworfen wird, wenn mindestens eine Bedingung einer Anzahl von Bedingungen erfüllt ist,

wobei die Anzahl von Bedingungen eine oder mehrere der folgenden Bedingungen umfasst:

- Alle Bildelemente in der Gruppe benachbarter Bildelemente sind außerhalb einer vordefinierten anatomischen Struktur (AS1) in dem zweiten Bild (I2);
- die Anzahl von Bildelementen in der Gruppe benachbarter Bildelemente ist geringer als ein vorbestimmter Wert;
- der mittlere Abstand der Bildelemente in der Gruppe benachbarter Bildelemente zu den zweiten Mittellinien (CL2) ist größer als ein vorbestimmter Schwellenwert;
- alle Bildelemente in der Gruppe benachbarter Bildelemente sind innerhalb einer vorbestimmten anatomischen Struktur (AS2) in dem zweiten Bild (I2);
- die maximale Röntgenopazität der Bildelemente in der Gruppe benachbarter Bildelemente ist geringer als ein vorbestimmter Schwellenwert;
- die Differenz der mittleren Röntgenopazität zwischen den Bildelementen in der Gruppe benachbarter Bildelemente und den Bildelementen in einer vordefinierten Umgebung um die Gruppe benachbarter Bildelemente ist größer als ein vorbestimmter Schwellenwert.

15. Verfahren nach einem der vorstehenden Ansprüche, wobei die Anzahl von in Schritt e) verarbeiteten Merkmalen eines oder mehrere der folgenden Merkmale umfasst:

- die Anzahl von Bildelementen in der entsprechenden verkalkten Kandidaten-Plaque (CCP);
- die mittlere Röntgenopazität der Bildelemente in der entsprechenden verkalkten Kandidaten-Plaque (CCP);
- die maximale Röntgenopazität der Bildelemente in der entsprechenden verkalkten Kandidaten-Plaque (CCP);
- die Anzahl von Bildelementen in der entsprechenden verkalkten Kandidaten-Plaque (CCP) oberhalb von einem oder mehreren Schwellenwerten der Röntgenopazität;
- die Anzahl von Bildelementen in der entsprechenden verkalkten Kandidaten-Plaque (CCP) oberhalb von einem oder mehreren Schwellenwerten der Röntgenopazität, normalisiert anhand der Anzahl von Bildelementen in der entsprechenden verkalkten Kandidaten-Plaque (CCP);
- die mittlere Röntgenopazität der Bildelemente in einer vordefinierten Umgebung um die entsprechende verkalkte Kandidaten-Plaque (CCP);
- die maximale Röntgenopazität der Bildelemente in einer vordefinierten Umgebung um die entsprechende verkalkte Kandidaten-Plaque (CCP);
- die Standardabweichung der Röntgenopazität der Bildelemente in einer vordefinierten Umgebung um die entsprechende verkalkte Kandidaten-Plaque (CCP);
- die Differenz der mittleren Röntgenopazität der Bildelemente in der entsprechenden verkalkten Kandidaten-Plaque (CCP) und der mittleren Röntgenopazität der Bildelemente in einer vordefinierten Umgebung um die entsprechende verkalkte Kandidaten-Plaque (CCP);
- die Differenz zwischen einem ersten Wert und einem zweiten Wert, wobei der erste Wert die Differenz zwischen der mittleren Röntgenopazität der Bildelemente in der entsprechenden verkalkten Kandidaten-Plaque (CCP) und der mittleren Röntgenopazität der Bildelemente in einer vordefinierten Umgebung um die entsprechende verkalkte Kandidaten-Plaque (CCP) ist und der zweite Wert die Standardabweichung der Röntgenopazität der Bildelemente in einer vordefinierten Umgebung um die entsprechende verkalkte Kandidaten-Plaque (CCP) ist;
- einen oder mehrere statistische Werte mit Bezug auf die Abstände entsprechender Bildelemente in der entsprechenden verkalkten Kandidaten-Plaque (CCP) zu dem nächsten Punkt der zweiten Mittellinien (CL2) in dem zweiten Bild (I2), wobei der nächste Punkt der Punkt ist, der am nächsten am entsprechenden Bildelement liegt;
- den Schwerpunkt der entsprechenden verkalkten Kandidaten-Plaque (CCP) in einem oder mehreren Koordinatensystemen.

16. Verfahren nach Anspruch 15, wobei der eine oder die mehreren statistischen Werte, die sich auf die Abstände der Bildelemente in dem entsprechenden verkalkten Kandidaten-Plaque (CCP) zu dem nächsten Punkt der zweiten Mittellinien (CL2) in dem zweiten Bild (I2) beziehen, einen oder mehrere der folgenden Werte umfassen:

- den Mittelwert der Abstände;
- die Standardabweichung der Abstände;
- den Maximalwert der Abstände;
- den Median der Abstände;
- die absolute Medianabweichung der Abstände vom Median der Abstände.

17. Vorrichtung zur rechnergestützten Analyse medizinischer Bilder, wobei ein Paar medizinischer Bilder analysiert wird, wobei das Paar ein erstes Bild (I1) aufweist, das ein kontrastierter Scan eines Teils in einem Körper eines Menschen oder Tiers ist, und ein zweites Bild (I2), das ein nativer Scan des gleichen Teils des Körpers eines Menschen oder Tiers ohne Kontrastmittel ist, wobei die Vorrichtung einen Programmcode umfassenden Rechner umfasst, ausgelegt zum Durchführen

- eines Schritts a), der ein Schritt des Identifizierens von einer oder mehreren anatomischen Strukturen (AS1, AS2) sowohl in dem ersten Bild (I1) als auch in dem zweiten Bild (I2) ist, ergebend eine Positionsinformation der einen oder mehreren anatomischen Strukturen (AS1, AS2) in den ersten und zweiten Bildern (I1, I2);
- eines Schritts b), der ein Schritt des Identifizierens erster Mittellinien (CL1) von Gefäßen in dem ersten Bild (I1) ist, ergebend eine Positionsinformation der ersten Mittellinien (CL1) in dem ersten Bild (I1);
- eines Schritts c), der ein Schritt des Identifizierens zweiter Mittellinien (CL2) von Gefäßen in dem zweiten Bild (I2) ist, entsprechend jeweiligen ersten Mittellinien (CL1) in dem ersten Bild (I1), ergebend eine Positionsinformation der zweiten Mittellinien (CL2) in dem zweiten Bild (I2), wobei die Identifizierung der zweiten Mittellinien (CL2) den Schritt der Abbildung der ersten Mittellinien (CL1) von dem ersten Bild (I1) auf das zweite Bild (I2) mittels Schätzens einer räumlichen Transformation von dem ersten Bild (I1) zu dem zweiten Bild (I2) umfasst, basierend auf der einen oder den mehreren identifizierten anatomischen Strukturen (AS1, AS2) in den ersten und zweiten Bildern (I1, I2);
- eines Schritts d), der ein Schritt des Extrahierens verkalkter Kandidaten-Plaques (CCP) in dem zweiten Bild (I2) ist;
- eines Schritts e), der ein Schritt des Identifizierens verkalkter Plaques (CP) aus den verkalkten Kandidaten-Plaques (CCP) durch einen maschinellen Lernklassifikator (RFC) ist, der eine Anzahl von Merkmalen der verkalkten Kandidaten-Plaques (CCP) verarbeitet;

wobei Schritt d) und/oder Schritt e) dafür ausgelegt sind, die Positionsinformation der zweiten Mittellinien (CL2) in dem zweiten Bild (I2) zu verwenden.

18. Vorrichtung nach Anspruch 17, wobei die Vorrichtung dafür ausgelegt ist, ein Verfahren nach einem der Ansprüche 2 bis 16 durchzuführen.

19. Rechnerprogrammprodukt, direkt in den internen Speicher eines digitalen Rechners ladbar, umfassend einen Programmcode zum Durchführen eines Verfahrens nach einem der Ansprüche 1 bis 16, wenn der Programmcode auf einem Rechner ausgeführt wird.

20. Rechnerprogramm, umfassend einen Programmcode zum Durchführen eines Verfahrens nach einem der Ansprüche 1 bis 16, wenn der Programmcode auf einem Rechner ausgeführt wird.

Revendications

1. Procédé mis en œuvre par ordinateur d'analyse assistée par ordinateur d'images médicales, dans lequel on analyse une paire d'images médicales, la paire comprenant une première image (I1), qui est un scan contrasté d'une partie d'un corps humain ou animal et une seconde image (I2), qui est un scan naturel de la même partie du corps humain ou animal sans agent de contraste, le procédé comprenant les stades de :

a) identification d'une ou de plusieurs structures (AS1, AS2) anatomiques au sein à la fois de la première image (I1) et de la seconde image (I2) se traduisant en une information de position de la une ou des plusieurs structures (AS1, AS2) anatomiques dans la première et la seconde images (I1, I2) ;
b) identification de premières lignes (CL1) centrales de vaisseaux dans la première image (I1), se traduisant en une information de position des premières lignes (CL1) centrales dans la première image (I1) ;
c) identification de secondes lignes (CL2) centrales de vaisseaux dans la seconde image (I2) correspondant à des premières lignes (CL1) centrales respectives dans la première image (I1), se traduisant en une information de position des secondes lignes (CL2) centrales dans la seconde image (I2), l'identification des secondes lignes (CL2) centrales comprenant le stade de mise en correspondance des premières lignes (CL1) centrales de la première image (I1) à la seconde image (I2) en estimant une transformée spatiale de la première image (I1) à la seconde image (I2) reposant sur la une ou les plusieurs structures (AS1, AS2) anatomiques identifiées dans la première et la seconde image (I1, I2) ;
d) extraction de plaques (CCP) calcifiées candidates dans la seconde image (I) ;
e) identification de plaques (CP) calcifiées parmi les plaques (CCP) calcifiées candidates par un classificateur

(RFC) à apprentissage machine traitant un certain nombre de caractéristiques des plaques (CCP) calcifiées candidates ;

dans lequel le stade d) et/ou le stade e) utilisent l'information de position des secondes lignes (CL2) centrales dans la seconde image (I2).

2. Procédé suivant la revendication 1, dans lequel les images (I1, I2) médicales sont des scans à trois dimensions et/ou des scans CT, en particulier, des scans CT à trois dimensions.

3. Procédé suivant la revendication 1 ou 2, dans lequel les images (I1, I2) médicales sont des scans d'un cœur humain ou animal, les premières et secondes lignes (CL1, CL2) centrales identifiées de vaisseaux se référant à des artères coronaires.

4. Procédé suivant la revendication 3, dans lequel la une ou les plusieurs structures (AS1, AS2) anatomiques identifiées comprennent le péricarde et/ou la racine de l'aorte du cœur humain ou animal.

5. Procédé suivant l'une des revendications précédentes, dans lequel on utilise un apprentissage d'espace marginal dans le stade a) pour identifier la une ou les plusieurs structures (AS1, AS2) anatomiques dans la première et la seconde images (I1, I2).

6. Procédé suivant l'une des revendications précédentes, dans lequel l'estimation de la transformée spatiale dans le stade c) repose sur le modèle mince plaque-spline ou sur un modèle de transformée affine.

7. Procédé suivant l'une des revendications précédentes, dans lequel, dans le stade d), des plaques (CCP) calcifiées candidates extraites respectives sont affectées chacune à un vaisseau précis, qui est le vaisseau ayant une seconde ligne (CL2) centrale, à laquelle la plupart des éléments d'image de la plaque (CCP) calcifiée candidate extraite respective ont la distance la plus petite.

8. Procédé suivant l'une des revendications précédentes, dans lequel, dans le stade d), on extrait aussi des plaques (CCP) calcifiées candidates de la première image (I1), la transformée spatiale au stade c) étant affinée sur la base des différences de position entre des plaques (CCP) calcifiées candidates correspondantes dans la première et la seconde image (I1, I2) et le procédé se poursuivant sur la base de l'information de position des secondes lignes (CL2) centrales déduites de la transformée spatiale affinée.

9. Procédé suivant la revendication 8, dans lequel l'affinement de la transformée spatiale dans le stade c) est tel que la distance minimum moyenne entre des plaques (CCP) calcifiées candidates correspondantes dans la première et la seconde image (I1, I2) est minimisée.

10. Procédé suivant la revendication 8 ou 9, dans lequel on effectue l'extraction des plaques (CCP) calcifiées candidates de la première image (I1) seulement si une première condition est satisfaite, la première condition étant, de préférence, telle que le nombre de plaques (CCP) calcifiées candidates extraites dans la seconde image (I2) dépasse un premier seuil déterminé à l'avance.

11. Procédé suivant l'une des revendications 8 à 10, dans lequel on effectue l'affinement de la transformée spatiale seulement si une deuxième condition est satisfaite, la deuxième condition étant, de préférence, telle que le nombre de plaques (CCP) calcifiées candidates extraites dans la première image (I1) dépasse un deuxième seuil déterminé à l'avance.

12. Procédé suivant l'une des revendications précédentes, dans lequel le classificateur (RFC) d'apprentissage machine est un classificateur forêt aléatoire ou une machine à vecteur d'appui ou une analyse de discriminant linéaire ou une régression logistique ou un arbre d'amplification probabiliste.

13. Procédé suivant l'une des revendications précédentes, dans lequel l'extraction de plaque calcifiée candidate du stade d) identifie, comme plaques (CCP) calcifiées candidates dans la seconde image (I2) des groupes d'éléments d'image voisins, dans lesquels chaque élément d'image a une radio-densité excédant une valeur déterminée à l'avance.

14. Procédé suivant la revendication 13, dans lequel l'identification des groupes d'éléments d'image voisins est une

identification provisoire, qui est écartée, si au moins une condition, parmi un certain nombre de conditions, est remplie, le nombre de conditions comprenant une ou plusieurs des conditions suivantes :

- tous les éléments d'image du groupe d'éléments d'image voisins sont à l'extérieur d'une structure (AS1) anatomique définie à l'avance dans la seconde image (I2) ;
- le nombre d'éléments d'image dans le groupe d'éléments d'image voisins est inférieur à une valeur déterminée à l'avance ;
- la distance moyenne des éléments d'image dans le groupe d'éléments d'image voisins aux secondes lignes (CL2) centrales est plus grande qu'un seuil déterminé à l'avance ;
- tous les éléments d'image dans le groupe d'éléments d'image voisins est à l'intérieur d'une structure (AS2) anatomique définie à l'avance dans la seconde image (I2) ;
- la radio-densité maximum des éléments d'image dans le groupe d'éléments d'image voisins est inférieure à une valeur déterminée à l'avance ;
- la différence moyenne de radio-densité entre les éléments d'image dans le groupe d'éléments d'image voisins et les éléments d'image dans un voisinage défini à l'avance autour du groupe d'éléments d'image voisins est plus grande qu'un seuil déterminé à l'avance.

15. Procédé suivant l'une des revendications précédentes, dans lequel le nombre de caractéristiques traitées dans le stade e) comprend l'une ou plusieurs des caractéristiques suivantes :

- le nombre d'éléments d'image dans la plaque (CCP) calcifiée candidate respective ;
- la radio-densité moyenne des éléments d'image dans la plaque (CCP) calcifiée candidate respective ;
- la radio-densité maximum des éléments d'image dans la plaque (CCP) calcifiée candidate respective ;
- le nombre d'éléments d'image dans la plaque (CCP) calcifiée candidate respective au-dessus d'une ou de plusieurs valeurs de seuil de radio-densité ;
- le nombre d'éléments d'image dans la plaque (CCP) calcifiée candidate respective au-dessus d'une ou de plusieurs valeurs de seuil de radio-densité normées par le nombre d'éléments d'image dans la plaque (CCP) calcifiée candidate respective ;
- la radio-densité moyenne des élément d'image dans un voisinage défini à l'avance autour de la plaque (CCP) calcifiée candidate respective ;
- la radio-densité maximum des éléments d'image dans un voisinage défini à l'avance autour de la plaque (CCP) calcifiée candidate respective ;
- l'écart-type de radio-densité des éléments d'image dans un voisinage défini à l'avance autour de la plaque (CCP) calcifiée candidate respective ;
- la différence entre la radio-densité moyenne des éléments d'image dans la plaque (CCP) calcifiée candidate respective et la radio-densité moyenne des éléments d'image dans un voisinage défini à l'avance autour de la plaque (CCP) calcifiée candidate respective ;
- la différence entre une première valeur et une deuxième valeur, la première valeur étant la différence entre la radio-densité moyenne des éléments d'image dans la plaque (CCP) calcifiée candidate respective et la radio-densité moyenne des éléments d'image dans un voisinage défini à l'avance autour de la plaque (CCP) calcifiée candidate respective et la deuxième valeur étant l'écart-type de radio-densité des éléments d'image dans un voisinage défini à l'avance autour de la plaque (CCP) calcifiée candidate respective ;
- une ou plusieurs valeurs statistiques se référant à la distance d'éléments d'image respectifs dans la plaque (CCP) calcifiée candidate respective au point le plus proche des secondes lignes (CL2) centrales dans la seconde image (I2), le point le plus proche étant le point le plus proche de l'élément d'image respectif ;
- le centre de gravité de la plaque (CCP) calcifiée candidate respective dans un ou dans plusieurs systèmes de coordonnées.

16. Procédé suivant la revendication 15, dans lequel la une ou les plusieurs valeurs statistiques se référant aux distances d'éléments d'image dans la plaque (CCP) calcifiée candidate respective au point le plus proche des secondes lignes (CL2) centrales dans la seconde image (I2) comprend une ou plusieurs des valeurs suivantes :

- la moyenne des distances ;
- l'écart-type des distances ;
- le maximum des distances ;
- la médiane des distances ;
- l'écart absolu médian des distances à la médiane des distances.

17. Installation d'analyse assistée par ordinateur d'images médicales, dans laquelle une paire d'images médicales est analysée, la paire comprenant une première image (I1), qui est un scan contrasté d'une partie d'un corps humain ou animal, et une seconde image (I2), qui est un scan naturel de la même partie du corps humain ou animal sans agent de contraste, l'installation comprenant un ordinateur comprenant un code de programme configuré pour effectuer :

- un stade a), qui est un stade d'identification d'une ou de plusieurs structures (AS1, AS2) anatomiques au sein à la fois de la première image (I1) et de la seconde image (I2) se traduisant en une information de position de la une ou des plusieurs structures (AS1, AS2) anatomiques dans la première et la seconde image (I1, I2) ;
- un stade b), qui est un stade d'identification de premières lignes (CL1) centrales de vaisseaux dans la première image (I1), se traduisant en une information de position des premières lignes (CL1) centrales dans la première image (I1) ;
- un stade c), qui est un stade d'identification de secondes lignes (CL2) centrales de vaisseaux dans la seconde image (I2) correspondant à des premières lignes (CL1) centrales respectives dans la première image (I1), se traduisant en une information de position des secondes lignes (CL2) centrales dans la seconde image (I2), l'identification des secondes lignes (CL2) centrales comprenant le stade de mise en correspondance des premières lignes (CL1) centrales de la première image (I1) à la seconde image (I2) en estimant une transformée spatiale de la première image (I1) à la seconde image (I2) reposant sur la une ou les plusieurs structures (AS1, AS2) anatomiques identifiées dans la première et la seconde image (I1, I2) ;
- un stade d), qui est un stade d'extraction de plaques (CCP) calcifiées candidates dans la seconde image (I2) ;
- un stade e), qui est un stade d'identification de plaques (CP) calcifiées parmi les plaques (CCP) calcifiées candidates par un classificateur (RFC) d'apprentissage machine traitant un certain nombre de caractéristiques des plaques (CCP) calcifiées candidates ;

dans laquelle le stade d) et/ou le stade e) est configuré pour utiliser l'information de position des secondes lignes (CL2) centrales dans la seconde image (I2).

18. Installation suivant la revendication 17, dans laquelle l'installation est configurée pour effectuer un procédé suivant l'une des revendications 2 à 16.

19. Produit de programme d'ordinateur pouvant être chargé directement dans la mémoire interne d'un ordinateur numérique, comprenant un code de programme pour effectuer un procédé suivant l'une des revendications 1 à 16, lorsque le code de programme passe sur un ordinateur.

20. Programme d'ordinateur comprenant un code de programme pour effectuer un procédé suivant l'une des revendications 1 à 16, lorsque le code de programme passe sur une ordinateur.

FIG 1

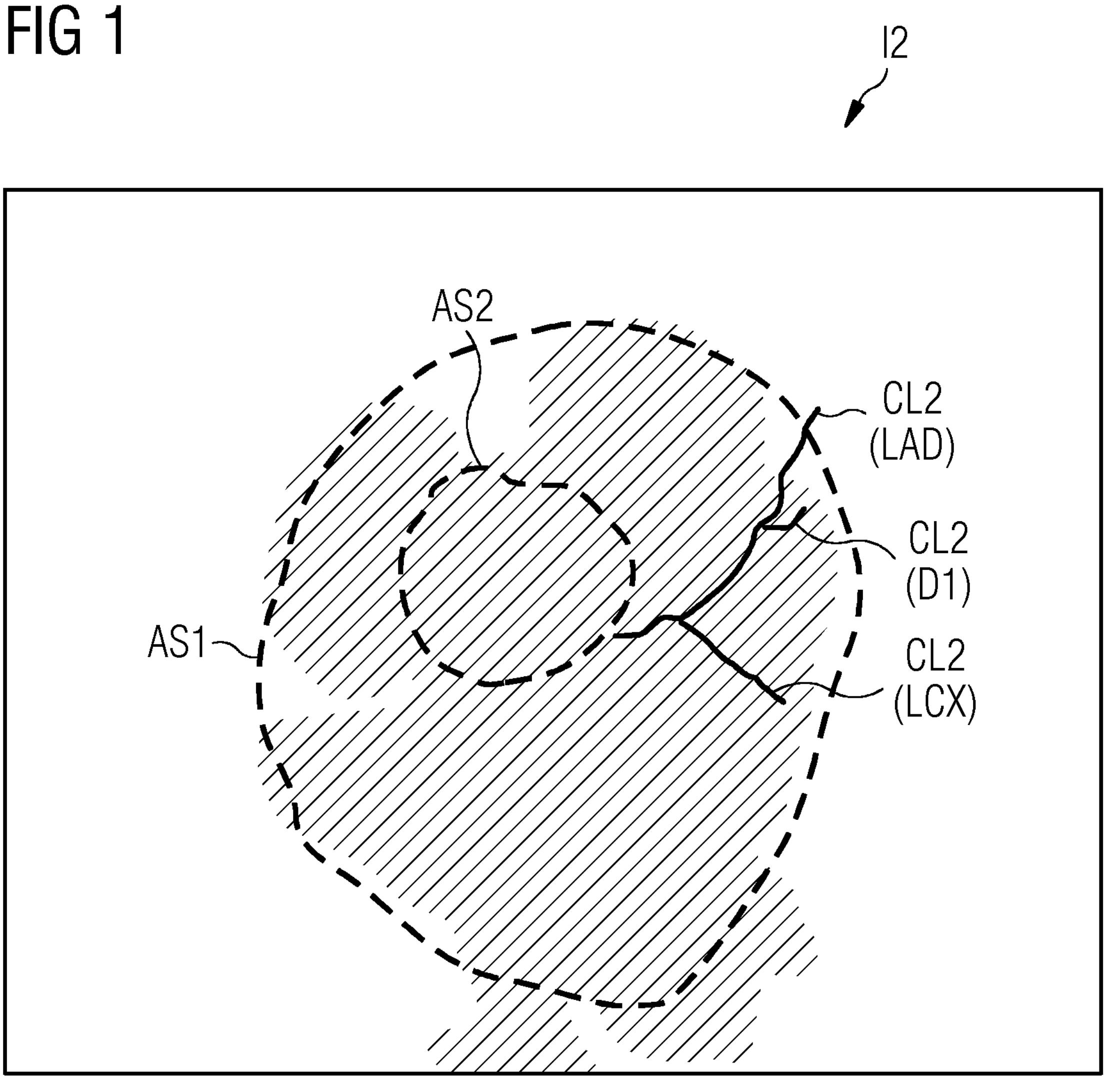
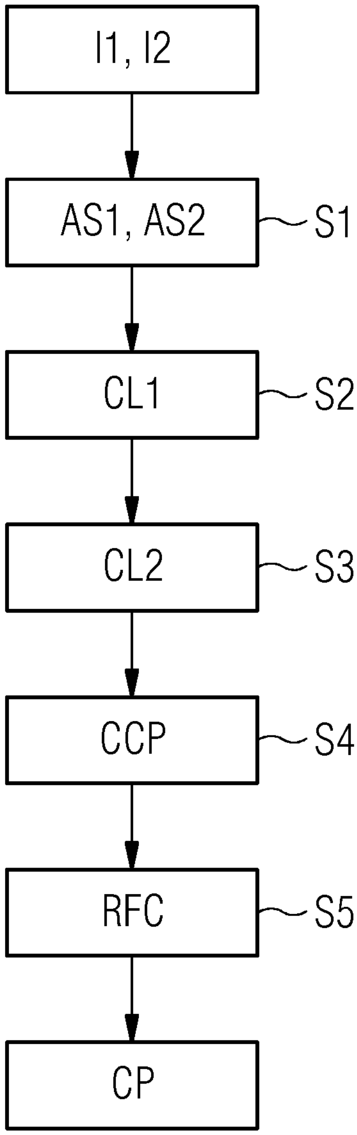


FIG 2



REFERENCES CITED IN THE DESCRIPTION

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专利名称(译)	基于计算机的医学图像分析程序		
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申请(专利权)人(译)	SIEMENS AKTIENGESELLSCHAFT		
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发明人	KELM, MICHAEL ZHENG, YEFENG		
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外部链接	Espacenet		

摘要(译)

本发明涉及一种用于医学图像的计算机辅助分析的方法，其中分析一对医学图像，该对医学图像包括第一图像（I1），该第一图像（I1）是人或动物体内的一部分的对比扫描，第二图像是第二图像。 图像（12），是对人体或动物同一部位进行的自然扫描。 在本发明的方法中，在第一图像（I1）和第二图像（I2）内都识别出解剖结构（AS1，AS2）。 通过使用那些解剖结构（AS1，AS2），第一图像（I1）中血管的中心线被映射到第二图像（I2）。 在第二图像（12）中提取候选钙化斑块（CCP），并通过机器学习分类器识别候选钙化斑块（CCP）中的钙化斑块（CCP）。 第二图像（12）中的中心线（CL2）的位置信息用于提取第二图像（12）中的候选钙化斑块（CCP）和/或从钙化的候选中识别钙化斑块（CCP） 机器学习分类器（CCP）。

FIG 1