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(54) **IMAGE RECONSTRUCTION AND PROCESSING**

(71) Applicant: **Commissariat à l'Energie Atomique et aux Energies Alternatives**, PARIS (FR)

(72) Inventor: **William GUICQUERO**, GRENOBLE (FR)

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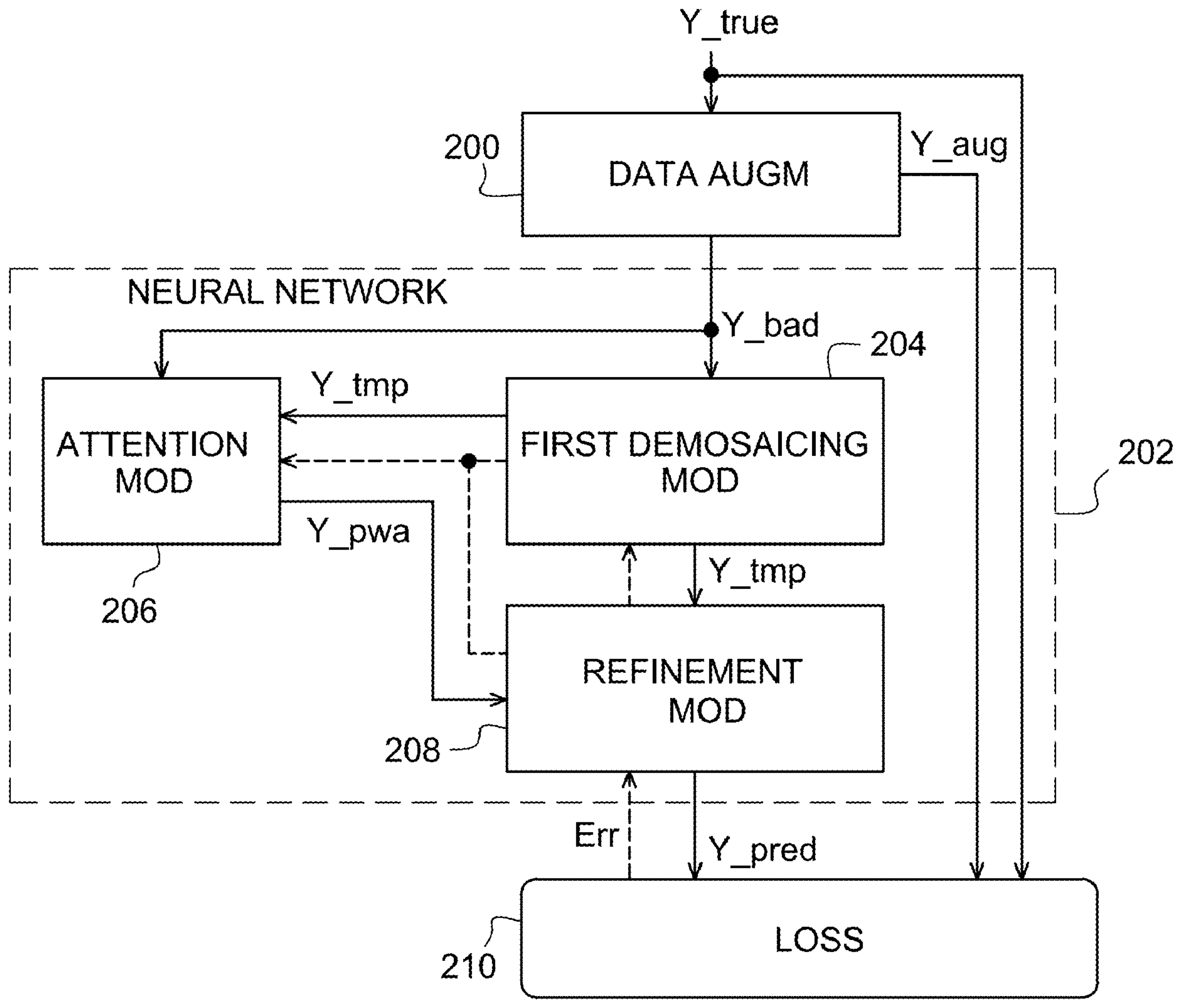
(57) **ABSTRACT**

The present description concerns a method of training a neural network (**202**) comprising: the generation of a modified image, by a modified data generator, based on a first image, the modified image comprising at least one outlier pixel value with respect to the first image; the supplying of the modified image to the network; the generation, by the network, of a corrected image; the supplying of the corrected image, by the network, and the supplying of an indication of the position of the at least one modified pixel, by the generator, to a computing circuit (**210**) the generation of an error value, based on the application of a loss function, by the computing circuit, taking as inputs the first image, the indication, and the corrected image; the correction of parameters associated with the network by backpropagation of the error in the network.



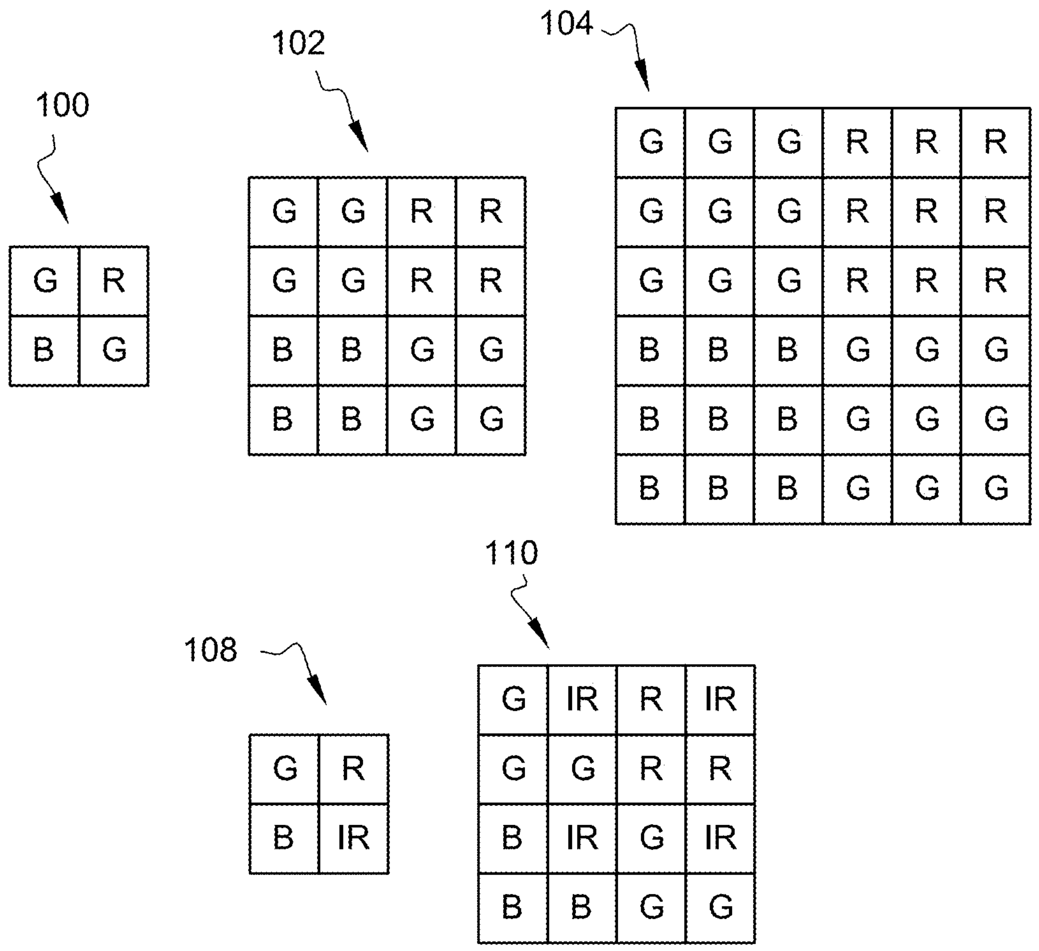

100
G R
B G
102
G G R R
G G R R
B B G G
B B G G
104
G G G R R R
G G G R R R
G G G R R R
B B B G G G
B B B G G G
B B B G G G
108
G R
B IR
110
G IR R IR
G G R R
B IR G IR
B B G G

Fig. 1

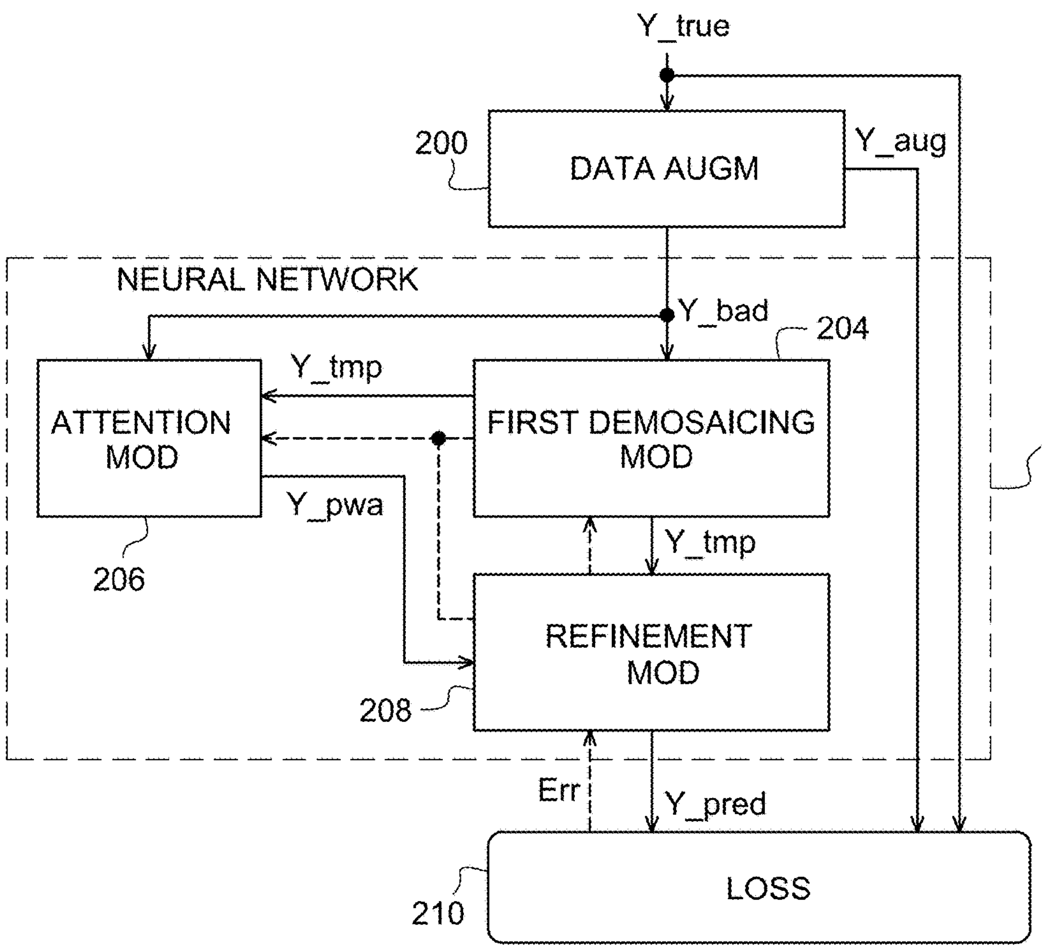

Y_true
200
DATA AUGM
Y_aug
NEURAL NETWORK
Y_bad
204
Y_tmp
ATTENTION MOD
FIRST DEMOSAICING MOD
202
Y_pwa
206
Y_tmp
REFINEMENT MOD
208
Err
Y_pred
LOSS
210

Fig. 2

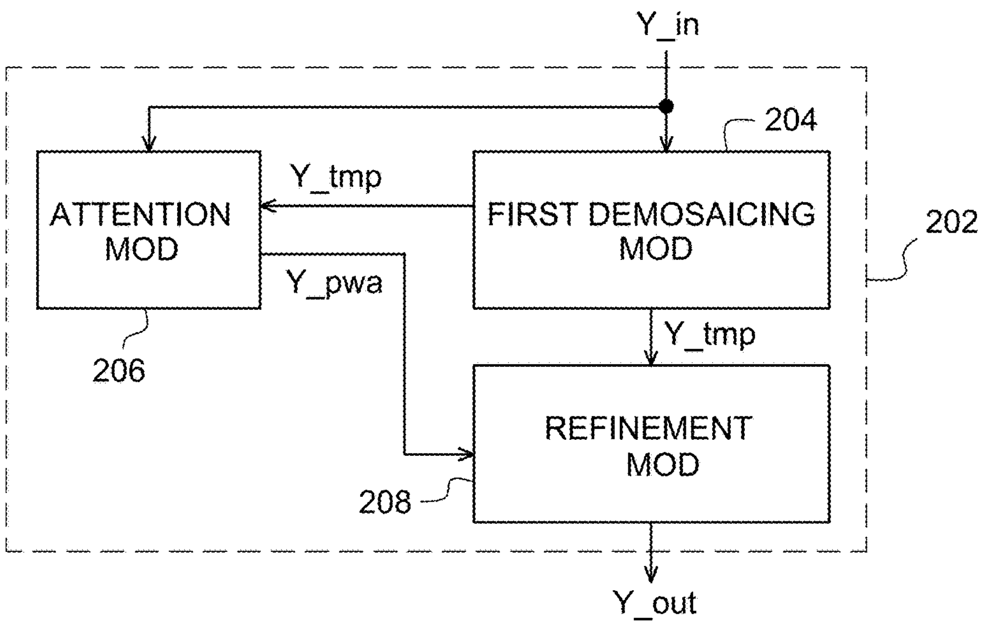

Y_in
204
ATTENTION MOD
Y_tmp
FIRST DEMOSAICING MOD
202
Y_pwa
206
Y_tmp
REFINEMENT MOD
208
Y_out

Fig. 3

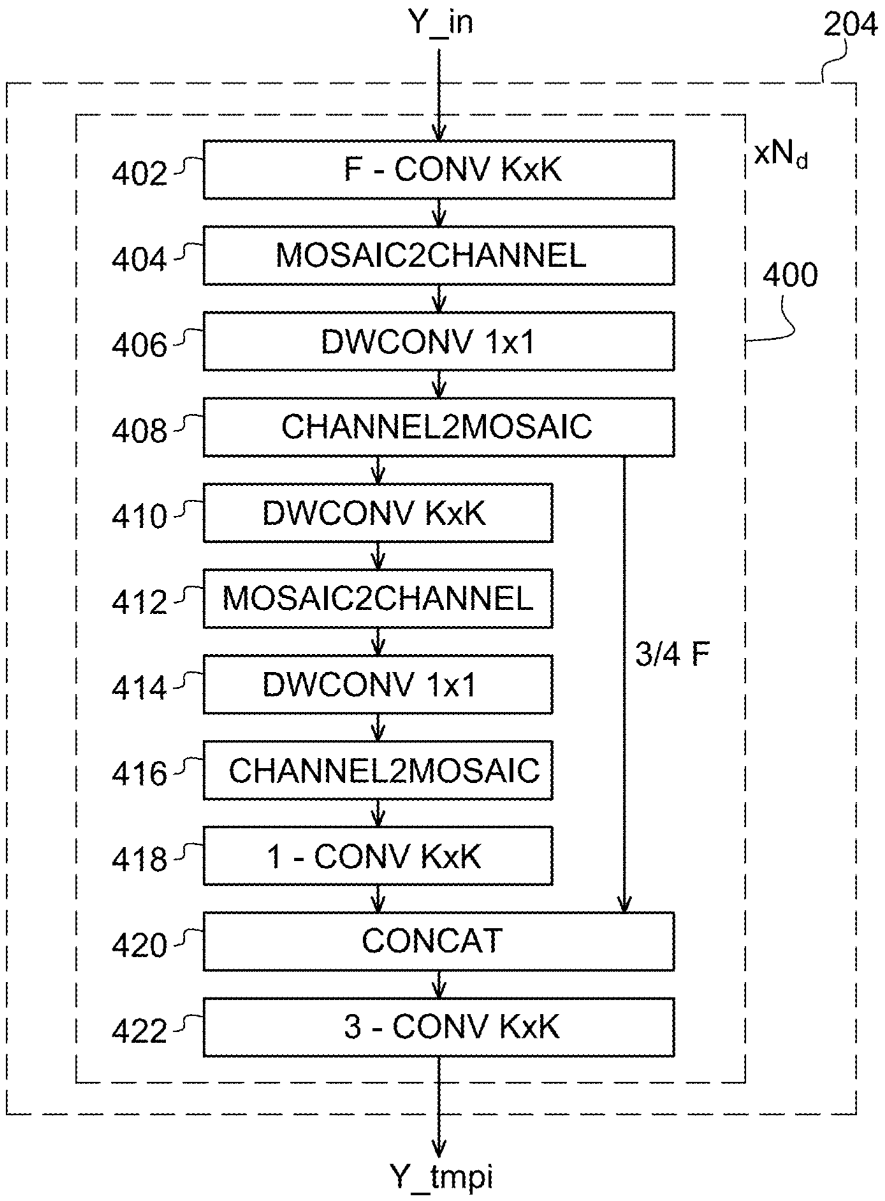

Y_in
204
402
F - CONV KxK
xN_d
404
MOSAIC2CHANNEL
400
406
DWCONV 1x1
408
CHANNEL2MOSAIC
410
DWCONV KxK
412
MOSAIC2CHANNEL
3/4 F
414
DWCONV 1x1
416
CHANNEL2MOSAIC
418
1 - CONV KxK
420
CONCAT
422
3 - CONV KxK
Y_tmpi

Fig. 4

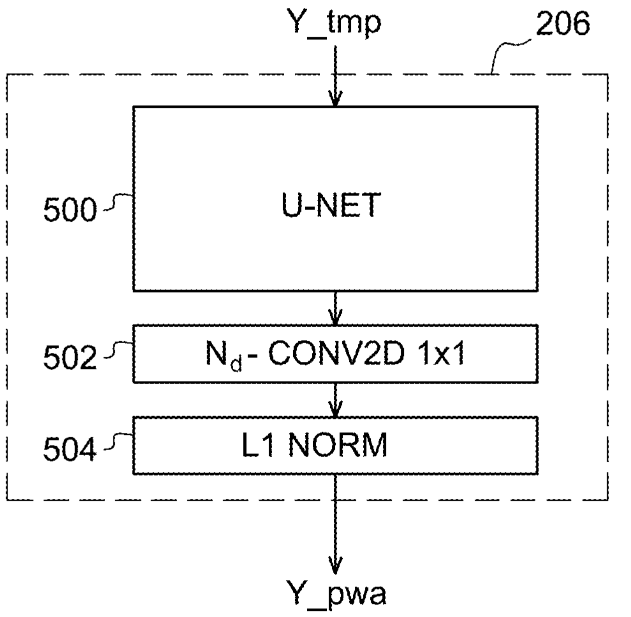


Fig. 5

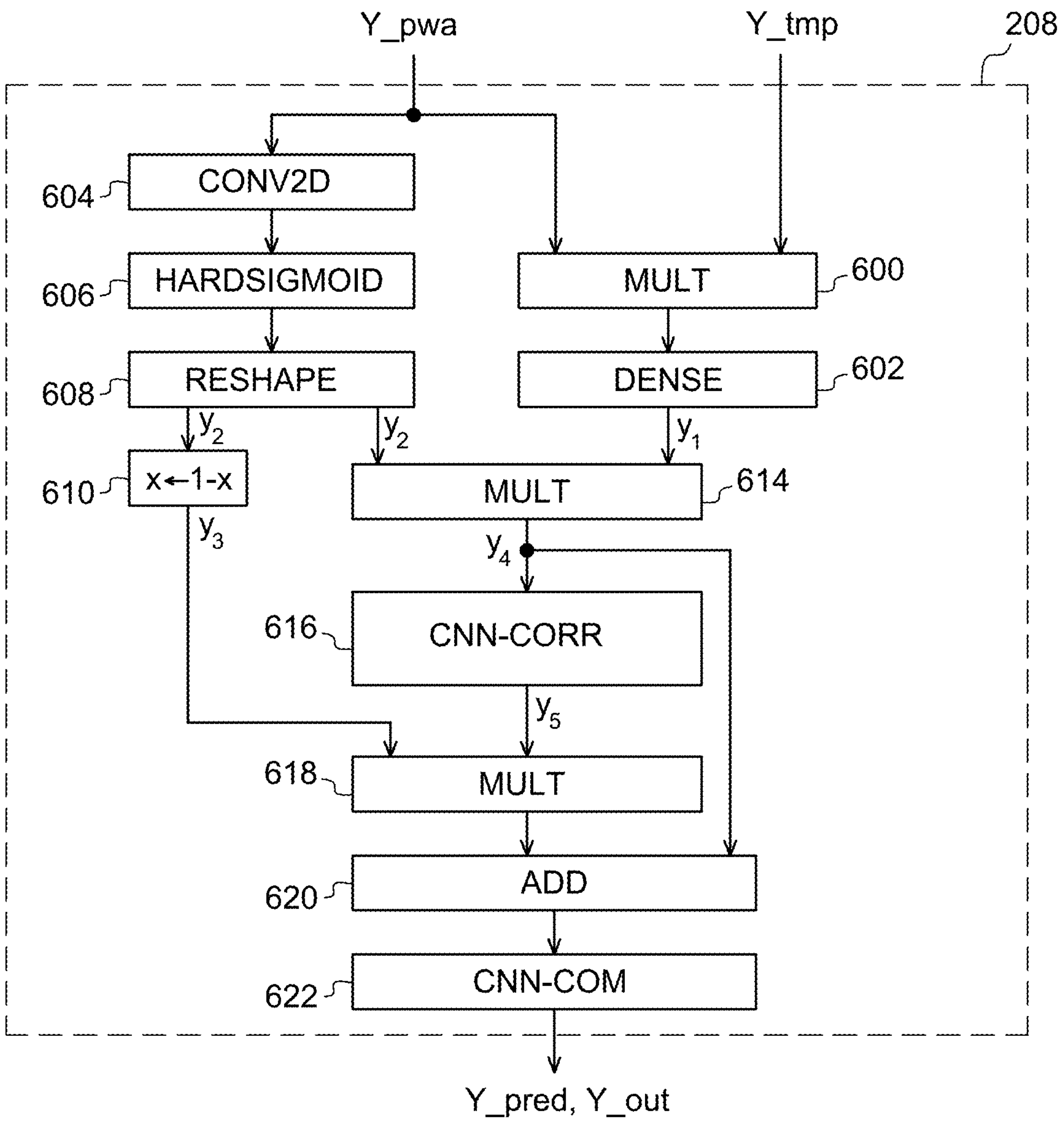

Y_pwa
Y_tmp
208
604
CONV2D
606
HARDSIGMOID
608
RESHAPE
MULT
600
DENSE
602
y_2
y_2
y_1
610
x←1-x
MULT
614
y_3
y_4
616
CNN-CORR
y_5
618
MULT
620
ADD
622
CNN-COM
Y_pred, Y_out

Fig. 6

IMAGE RECONSTRUCTION AND PROCESSING

FIELD

[0001] The present disclosure generally concerns methods and devices for the reconstruction and the processing of images, and in particular methods and devices for image demosaicing.

BACKGROUND

[0002] In Raw images acquired by image sensors, such as for example image sensors dedicated to visible and/or infrared imaging, exhibit alterations due to malfunctions of the sensors. In particular, image sensors implementing canonical imaging systems, using unit pixel mosaicing methods, may exhibit, within their lifetime, malfunctions on isolated pixels, or on pixel columns and/or losses of captured data for isolated pixels or pixel columns.

[0003] It is desirable to improve the processing and the reconstruction of images acquired by sensors comprising dysfunctional pixels.

SUMMARY

[0004] An embodiment provides a method of training a neural network configured to perform image processing operations, the method comprising:

- **[0005]** the generation of a modified image, by a modified data generator, based on a first image, the modified image comprising at least one outlier pixel value with respect to the first image;
- **[0006]** the supplying of the modified image to the network;
- **[0007]** the generation, by the network, of a corrected image;
- **[0008]** the supplying of the corrected image, by the network, and the supplying of an indication of the position of the at least one modified pixel, by the generator, to a computing circuit
- **[0009]** the generation of an error value, based on the application of a loss function, by the computing circuit, taking as inputs the first image, the indication, and the corrected image;
- **[0010]** the correction of parameters associated with the network by backpropagation of the error in the network.

[0011] According to an embodiment, the generation of the corrected image by the network comprises:

- **[0012]** the generation, by a first sub-module, of an intermediate data value based on the modified image, the intermediate data item being an at least partial reconstruction of the first image;
- **[0013]** the generation, by a second sub-module of the network, of an attention data item based on one of the intermediate data item and/or of the modified image, the attention data item comprising an estimate of the location of the at least one modified pixel;
- **[0014]** the generation of the corrected image, by the first sub-circuit or by a third sub-circuit, based on the intermediate data item and on the indication data item.

[0015] According to an embodiment, the generation of the attention data item comprises the execution of a convolutional neural network configured for image segmentation, based on the intermediate data item and/or on the corrected image.

[0016] According to an embodiment, the convolutional neural network is a network of U-net type or a variant of network of U-net type.

[0017] According to an embodiment, the generation of the attention data further comprises a normalization of NL1 standard type, based on the data item generated by the convolutional neural network.

[0018] According to an embodiment, the generation of the corrected image comprises a multiplexing operation and/or a multiplication operation, for example a pointwise multiplication, based on the attention data item and on the intermediate data item.

[0019] According to an embodiment, the generation of an error value comprises the application of a focal loss function taking, as input data, the modified image, the first image, and the indication of the location of the at least one modified pixel.

[0020] According to an embodiment, the generation of an error value further comprises the application:

- **[0021]** of a loss function based on an averaging taking, as input data, the modified image and the first image; and/or
- **[0022]** of a regularization function taking, as input data, the modified image.

[0023] According to an embodiment, the first image is comprised in a database.

[0024] According to an embodiment, the generation of the modified image comprises, for each pixel:

- **[0025]** the determination of whether the pixel is to be modified; and
- **[0026]** if the pixel is to be modified, the replacing of the value associated with the pixel by an outlier.

[0027] According to an embodiment, the generation of the modified image, by the modified data generator, is further performed based on a mosaic pattern.

[0028] According to an embodiment, the model of the modified data generator is a neural network model previously trained for modified image generation, and configured for the implementation of so-called "style transfer" techniques.

[0029] An embodiment provides an image processing method comprising:

- **[0030]** the capturing of an image scene, by an imager of an image processing device, the captured image being an image mosaiced according to a mosaic pattern
- **[0031]** the supplying of the mosaiced image to a neural network of the processing device trained according to the above training method; and
- **[0032]** the generation of a corrected image, by the network, based on the mosaiced image.

[0033] According to an embodiment, the generation of the corrected image by the network comprises:

- **[0034]** the supplying of the mosaiced image to a first sub-module of the network configured to generate an intermediate data item by performing a first demosaicing of the mosaiced image;
- **[0035]** the supplying of the intermediate data item to a second sub-module of the network configured to generate an attention data item based on the intermediate

data item, the attention data item comprising estimates of the location of dysfunctional pixels of the imager; and

[0036] the generation of the corrected image, by a third sub-module, based on the intermediate data item and on the attention data item.

[0037] According to an embodiment, the mosaic pattern corresponds to a mosaic pattern used during the generation of a modified image during the training of the network.

[0038] An embodiment provides an image processing device comprising:

[0039] an imager configured to capture image scenes, according to a mosaic pattern;

[0040] a neural network trained according to the above training method, configured to generate a corrected image based on the mosaiced image.

[0041] According to an embodiment, the imager comprises one or a plurality of dysfunctional pixels.

BRIEF DESCRIPTION OF THE DRAWINGS

[0042] The foregoing features and advantages, as well as others, will be described in detail in the rest of the disclosure of specific embodiments given as an illustration and not limitation with reference to the accompanying drawings, in which:

[0043] FIG. **1** shows examples of mosaic patterns implemented by image sensors;

[0044] FIG. **2** is a block diagram illustrating a neural network training architecture, according to an embodiment of the present disclosure;

[0045] FIG. **3** is a block diagram illustrating a architecture of the network configured to perform inference operations, according to an embodiment of the present disclosure;

[0046] FIG. **4** is an example of architecture of a processing network, according to an embodiment of the present disclosure;

[0047] FIG. **5** is an example of architecture of an attention module, according to an embodiment of the present disclosure; and

[0048] FIG. **6** is an example of architecture of a processing network, according to an embodiment of the present disclosure.

DETAILED DESCRIPTION OF THE PRESENT EMBODIMENTS

[0049] Like features have been designated by like references in the various figures. In particular, the structural and/or functional features that are common among the various embodiments may have the same references and may dispose identical structural, dimensional and material properties.

[0050] For clarity, only those steps and elements which are useful to the understanding of the described embodiments have been shown and are described in detail. In particular, the operation and the implementation of different types of neural network layers, such as dense layers, convolutional layers, etc., are not described in detail and are known to those skilled in the art.

[0051] Unless indicated otherwise, when reference is made to two elements connected together, this signifies a direct connection without any intermediate elements other than conductors, and when reference is made to two elements coupled together, this signifies that these two elements can be connected or they can be coupled via one or more other elements.

[0052] In the following description, where reference is made to absolute position qualifiers, such as "front", "back", "top", "bottom", "left", "right", etc., or relative position qualifiers, such as "top", "bottom", "upper", "lower", etc., or orientation qualifiers, such as "horizontal", "vertical", etc., reference is made unless otherwise specified to the orientation of the drawings.

[0053] Unless specified otherwise, the expressions "about", "approximately", "substantially", and "in the order of" signify plus or minus 10%, preferably of plus or minus 5%.

[0054] FIG. **1** examples of mosaic patterns implemented by image sensors, or imagers.

[0055] A mosaic pattern is a pattern comprising a plurality of pixels and acting as a replicated spectral filter, mosaic, on the surface of an imager. The imager then measures, for each pixel in the mosaic, a value associated with a channel defined by the mosaic pattern. The mosaic pattern indicates, for each pixel, which single channel among, for example, color and/or infrared channels is measured. As an example, each pixel has a spectral signature determining a wavelength interval comprising the spectral response recorded by the pixel.

[0056] In the example of FIG. **1**, a mosaic pattern **100** is a Bayer-type pattern. This pattern has a 2×2-pixel size and enables to measure the wavelengths associated with the green color (G) for the pixels at the top left and at the bottom right of the pattern. The Bayer pattern further enables to measure the wavelengths associated with the red color (R) of the pixel at the top right, as well as to measure the wavelengths associated with the blue color (B) at the bottom left of the pattern.

[0057] A mosaic pattern **102** is a QuadBayer-type pattern. This pattern has a 4×4-pixel size and enables to measure the wavelengths associated with the green color (G) for the four pixels at the top left and at the bottom right of the pattern. Pattern **102** further enables to measure the wavelengths associated with the red color (R) for the pixels at the top right, and as well as to measure the wavelengths associated with the blue color (B) for the four pixels at the bottom left of the pattern.

[0058] A pattern **104** is a pattern of 3-cell Bayer type. This pattern has a 6×6-pixel size and has the same structure as patterns **100** and **102**, except that the red, green, and blue color channels are measured in groups of 3×3 pixels.

[0059] A pattern **108** is a pattern of 2×2 RGBIR type. This pattern has a 2×2-pixel size and enables to measure the wavelengths associated with the green color for the pixel at the top left of the pattern. Pattern **108** further enables to measure the wavelengths associated with the blue color of the pixel at the top right, and to measure the wavelengths associated with the red color at the bottom left of the pixel. Pattern **108** further enables to measure the wavelengths associated with the infrareds (IR) of the pixel at the bottom right.

[0060] A pattern **110** is a pattern of 4×4 RGBIR type. This pattern has a 4×4-pixel size and enables to measure the wavelengths associated with the green color of the first pixel, starting from the left in the first row, of the third pixel, starting from the left in the third row, of the first and second pixels, starting from the left in the second row, and of the third and fourth pixels, starting from the left in the fourth row. Pattern **110** further enables to measure the wavelengths associated with infrareds of the second and fourth pixels, starting from the left of the first and third rows. Pattern **110** further enables to measure the wavelengths associated with the blue color of the first pixel, starting from the left of the third row, and of the first and second pixels, starting from the left of the fourth row, as well as to measure the wavelengths associated with the red color of the third pixel, starting from the left of the first row, and of the third and fourth pixels, starting from the left of the second row.

[0061] These examples of mosaic patterns are given as an example and are of course not limiting. Other mosaic patterns having different size and arrangements may of course be envisaged. In other examples, the mosaic pattern replicated on the imager surface comprises a pixel configured to measure a distance between one or a plurality of targets in the captured scene and the imager. Such imagers are color image sensors further enabling to capture so-called depth information, it is then spoken of monolithic RGBZ imagers.

[0062] A raw image captured by the imager comprises, for example, for each pixel, a single measured value. The demosaicing then consists of estimating, for each pixel, the value of the non-measured channels by using, for example, the spectral correlation between the measured channels as well as the spatial correlation between the value of a same channel for two adjacent pixels.

[0063] However, there may happen for certain pixels to be dysfunctional. As an example, one or a plurality of isolated pixels may become saturated or unusable. It will then be spoken of a dead pixel. As an example, the so-called dark signal, representing a type of noise in the absence of a luminous flux, measured for isolated pixels is outside the nominal statistics, and the measurements associated with these pixels are then aberrant. Other noise sources may cause an aberrant behavior on a pixel or on a group of pixels. As an example, certain isolated pixels are subject to random telegraphic signal (RTS) noise. As an example, as a result of a malfunction of an imager readout circuit, pixel columns are missing, or clamped. In other examples, a digital fault, such as for example a loss of synchronization in measurements, or a bit-flip, causes a loss of data associated with isolated pixels and/or columns and/or rows of pixels and/or one or a plurality of pixel frames. In the following, there will be called bad pixel any dysfunctional pixel, whether it is isolated or in a dysfunctional column, row, or frame. Measurements associated with bad pixels are then aberrant or outlier measurements, not approaching reality.

[0064] Further, bad pixels will, for example, influence the estimation of adjacent pixels during demosaicing. As an example, the final image, obtained as a result of a demosaicing which does not correct bad pixels, will for example exhibit black spots having a greater size than the bad pixel or the group of bad pixels

[0065] However, outlier measurements associated with bad pixels are relatively infrequent. Indeed, the above-mentioned malfunctions generally have a low occurrence rate, in the order of 1/1000 or less. However, in imagers comprising a very large number of pixels, these malfunctions may be impacting in terms of on visual rendering and for the perception of the image. As an example, these malfunctions impact image rendering in much more visible fashion than disturbances due to homoscedastic noise having a distribution centered around zero.

[0066] When a deep neural network is trained to demosaic raw images, outlier measurements, associated with bad pixels, are drowned out by other noise, due to their rare occurrence. Further, conventional loss functions, mainly based on average calculations and canonically applying regardless of the pixel position, fail to identify and correct this type of outliers.

[0067] FIG. **2** is a block diagram illustrating a training architecture of a deep neural network, according to an embodiment of the present disclosure. In particular, the training of the neural network described in relation with FIG. **2** enables to taken into account outliers, for example due to bad pixels, in image reconstruction.

[0068] According to an embodiment, an augmentation module **200** (DATA AUGM) enables, for example, the execution of a data augmentation model. As an example, module **200** is configured to receive, as input data, an image Y_true corresponding to a ground truth, that is, to an image comprising no error resulting from any processing. As an example, each pixel of image Y_true comprises the ground truth values of a plurality of channels. Module **200** is further configured to generate a modified image Y_bad, based on image Y_true. The modified image Y_bad then corresponds to image Y_true, in a mosaic format, to which are added one or a plurality of outliers.

[0069] As an example, module **200** is configured to model noise such as pixel readout and column readout noise, photonic noise, fixed pattern noise, for example structured, random telegraphic noise, and dead or saturated pixels.

[0070] As an example, module **200** is configured to add to each pixel, with a probability at most equal to 1/1,000, an outlier. In other words, module **200** performs, pixel by pixel, a Bernoulli test, with parameter p, where p is at most equal to 1/1,000. When the Bernoulli test is successful, module **200** is configured to modify the value of the associated pixel into an outlier. When the test fails, in the majority of cases, the pixel value remains identical to that of image Y_true. In another example, when the test fails, one or a plurality of noises are added to the pixel value. As an example, the outlier is a constant value. In another example, the outlier originates, for each concerned pixel, from a random draw. The outlier is for example added to the value measured for said pixel. In another example, the outlier is multiplied by the value measured for said pixel. Still in another example, the outlier is substituted for the value measured for said pixel. In another example, for each concerned pixel, a plurality of outliers are for example determined, randomly or not, and the measured value of the pixel is replaced with a combination of at least one addition of an outlier with the measured value and/or of a multiplication of an outlier by the measured value.

[0071] As an example, the generation of the outlier is performed according to a strongly pitted probability distribution, that is, having a high 4th-order moment, such as for example a Laplace distribution, a Cauchy distribution, etc.

[0072] The methods and circuits for the generation of such a modified image are known to those skilled in the art, and the given example of generation is of course not limiting.

[0073] Module **200** is further configured to generate a data item Y_aug, for example taking the form of a tensor, comprising indications of the positions of the modified pixels. As an example, data item Y_aug further comprises an indication of the outliers having been assigned.

[0074] As an example, the field images, supplied to module **200** are comprised in a pre-stored database, for example in a non-volatile memory, such as a server, etc.

[0075] Module **200** is for example configured to supply the modified image Y_bad to a neural network **202** (NEURAL NETWORK) in order to train it. As an example, network **202** is configured to perform regression tasks in order to reconstruct and demosaic a mosaiced image being supplied thereto, while taking into account possible bad pixels. As an example, network parameters, such as weights etc., are initially set to initial values.

[0076] According to an embodiment, the mosaic pattern used by module **200** to mosaic image Y_true corresponds to the mosaic pattern which will be used by an image sensor of a device comprising trained network **202**.

[0077] According to another embodiment, module **200** comprises a neural network previously trained to generate images, such as for example mosaiced images. As an example, image generation is performed by means of so-called "style transfer" techniques, such as, for example, the techniques described in the publication "Unsupervised Image-to-Image Translation: A review" by Hoyer, H. et al. and published in Sensors in **2022** and/or in the popularization article on GAN cycles "A Gentle Introduction to CycleGAN for Image Translation" written by Brownlee, J., Aug. 17, 2017.

[0078] Network **202** comprises, for example, a processing sub-module **204** (FIRST DEMOSAICING MODULE) configured to generate an intermediate data item Y_tmp, based on the modified image Y_bad. The intermediate data item Y_tmp corresponds, for example, to a first demosaicing and reconstruction of the image. As an example, module **204** is a convolutional network integrating a plurality of neural layers.

[0079] Network **202** further comprises, for example, an attention sub-module **206** (ATTENTION MOD) configured to receive the intermediate data item Y_tmp, or a sub-part thereof, supplied by module **204** and/or the modified image Y_bad supplied by augmentation module **200**. Sub-module **206** is further configured to generate an attention data item Y_pwa having, for example, the form of a tensor. Data item Y_pwa is generated by sub-module **206** so as to carry the information of the modified image pixel by pixel. In particular, sub-module **206** is designed to implement, first, a pixel-by-pixel segmentation of the image, in order to determine pixel by pixel a type of demosaicing to be performed. Sub-module **206** is further configured to generate data item Y_pwa in such a way that it comprises information about a type of processing to be carried out pixel by pixel, such as for example a gating operation. The gating is for example performed on the data of tensor Y_tmp by means of signal Y_pwa, in order to weight each type of reconstruction present in tensor Y_tmp according to tensor Y_pwa.

[0080] Network **202** for example further comprises a refinement sub-module **208** (REFINEMENT MOD). As an example, sub-module **208** is configured to generate a corrected image Y_pred based on the intermediate data item Y_tmp supplied by sub-module **204** and on the attention data item Y_pwa supplied by sub-module **206**.

[0081] In another example, sub-module **208** is configured to perform an Y_tmp gating in the axis of the channels, based on data item Y_pwa.

[0082] During the training of network **202**, the corrected image Y_pred is supplied to a computing circuit **210** (LOSS). Computing circuit **210** is further configured to receive ground truth image Y_true and the data item Y_aug comprising the indications of the positions where the outliers have been added by module **200**.

[0083] As an example, data item Y_aug is a tensor having a value in \{0,1\}, the pixels assigned to value 1 indicating for example the positions of bad pixels.

[0084] According to an embodiment, computing circuit **210** is configured to calculate an error value Err by applying a loss function to the modified image Y_pred, ground truth image Y_true, and data item Y_aug. As an example, the loss function applied by calculation circuit **210** combines a plurality of fidelity loss functions, such as a loss function based on mean error calculations without bias and applied between data Y_pred and Y_true, or a focal loss function (LFF) applied to the data Y_pred, Y_true, and Y_aug for which the focusing is, for example, controlled by tensor Y_aug. As an example, the loss function applied by computing circuit **210** further comprises a regularization function applied only to the corrected image Y_pred. As an example, the regularization function is determined based on assumptions as to the nature of the signal of the corrected image Y_pred.

[0085] As an example, the error value is such that Err=λ_{LFM}×LFM(Y_pred, Y_true)+λ_{LFF}×LFF(Y_pred, Y_true, Y_aug)+λ_{LR}×LR(Y_pred) where function LFM is a loss function based on mean error calculations, for example based on mean square error calculation, function LFF is a focal loss function, and function LR is a regularization function, and where λ_{LFM}, λ_{LFF}, and λ_{LR} are weighting coefficients. For example, coefficients λ_{LFM}, λ_{LFF}, and λ_{LR} are used to emphasize the importance of one loss function over another.

[0086] As an example, the mean error LFM(Y_pred, Y_true) is such that

$$LFM(\mathrm{Y\_pred}, \mathrm{Y\_true}) = \lambda_1 \sum |CNN(\mathrm{Y\_pred}) - CNN(\mathrm{Y\_true})| + \lambda_2^2 \sqrt{|CNN(\mathrm{Y\_pred}) - CNN(\mathrm{Y\_true})|^2}, \quad \text{[Math 1]}$$

where CNN (•) is an intermediate output of a neural network model having been previously trained to perform certain inference tasks. As an example, CNN(•) has been trained in supervised fashion so as to feed a sub-model dedicated to image classification tasks. For example, the neural network is based on a latent space derived from a neural network model trained to perform classification operations on databases, such as for example the ImageNET database. As an example, function CNN(•) is a function vgg(•) where vgg(•) is a function returning a latent space, for example of type vgg16, coefficients λ_1 and λ_2 are weighting coefficients between distance calculations of L1 and L2 type. In particular, the sum is performed on all elements, that is, on all pixels and all channels.

[0087] As an example, the focal error LFF(Y_pred, Y_true, Y_aug) is such that:

$$LFF(\mathrm{Y\_pred}, \mathrm{Y\_true}, \mathrm{Y\_aug}) = \sum ((\mathrm{dilate}(\mathrm{Y\_aug})) \odot (\mathrm{Y\_pred} - \mathrm{Y\_true}))^2, \quad \text{[Math 2]}$$

where dilate(•) defines a morphological dilation function, for example having a 5×5 circular kernel, and where the operator ⊙ corresponds to point-by-point multiplication. In particular, function dilate(•) enables to increase the radius of impact of the loss function in the vicinity of outlier pixels, then enabling to more easily correct effects due to large receptive fields of the convolutional neural network used to reconstruct the image.

[0088] As an example, the regularity error LR(Y_pred) is such that:

$$LR(\text{Y\_pred}) = TV(\text{Y\_pred}), \qquad \text{[Math 3]}$$

where TV(•) corresponds, for example, to the calculation of the total variation, or to a variant of the total variation. The use of the total variation as a regularization function is given as an example and is of course not limiting.

[0089] According to an embodiment, during the training of network **202**, the obtained error value is backpropagated in network **202** in order to re-evaluate and update the parameters associated with network **202**. As an example, the update of the parameters is performed by the implementation of a gradient backpropagation method based on the error value. Deep learning methods based on gradient backpropagation are known to those skilled in the art and are thus not described in greater detail herein.

[0090] According to an embodiment, the focal loss function has the role of indicating to network **202**, during the backpropagation of the error, which pixels are highly noisy. As an example, coefficient λ_{LFF} is greater than coefficient λ_{LFM}.

[0091] FIG. **3** is a block diagram illustrating an architecture of network **202** configured to perform regression operations, according to an embodiment of the present disclosure.

[0092] As an example, once trained, network **202** is implemented in an image processing device. As an example, the processing device further comprises an imager (not shown) configured to capture image scenes based on a mosaic pattern such as for example one of the patterns **100**, **102**, **104**, **108**, or **110** described in relation with FIG. **1**. As an example, the imager comprises one or a plurality of bad pixels, or dysfunctional pixels. As an example, the device is a camera, a camcorder, a smartphone, etc.

[0093] Once the training of network **202** is over, that is, at the end of the implementation of the training described in relation with FIG. **2** on a plurality of ground truth images Y_true, network **202** is for example configured to perform regression operations on an input image Y_in, replacing data Y_bad, for example comprising one or a plurality of bad pixels. As an example, the training is over at the end of the processing of a large number, for example at least 1,000, of ground truth images. In another example, the training ends when the learning algorithm converges, that is, when the error value becomes lower than a threshold value.

[0094] The regression operation performed by the trained network **202** then consists in generating a demosaiced and reconstructed image Y_out based a mosaiced input image Y_in, supplied for example by the imager. The trained network **202** then comprises, for example, sub-modules **204**, **206**, and **208**, having their parameters set at the end of the training. The mosaiced image Y_in is then directly supplied to network **202**, without passing through augmentation module **200**. Similarly, the demosaiced and reconstructed image Y_out is not supplied to computing circuit **210**. Augmentation module **200** and computing circuit **210** are not, for example, part of the processing device in which the trained network **202** is implemented.

[0095] The trained network **202** is then configured, for example, to perform regression, interpolation, denoising, and detection and correction operations on the bad pixels detected in input image Y_in and to generate the corrected image Y_out based on these operations. In particular, as a result of the training, the processing sub-module **204** of network **202** is for example configured to generate an intermediate data item Y_tmp by making a first estimate of the missing or noisy information, at least partly due to bad pixels.

[0096] As a result of the training, sub-module **206** is configured, for example, to generate an attention data item Y_pwa, based on input image Y_in and/or on intermediate data item Y_tmp. Sub-module **206** is then for example configured to detect, individually for each pixel, whether this pixel is a bad pixel or not. The success rate of the bad pixel detection depends, of course, on the training and on the level of expressivity, linked to its internal structure, of network **202**. Sub-module **206** then generates a data item Y_pwa, comprising information on the detected outliers as well as on their location in input image Y_in. As an example, the detection is a multi-scale detection and data item Y_pwa provides a context, for example a category indication among, among others, a type of contour, texture, presence, and noise level and of positions of the outlier pixels, pixel by pixel.

[0097] As a result of the training, sub-module **208** is configured, for example, to generate the demosaiced image Y_out based on intermediate data item Y_tmp and on attention data item Y_pwa. As an example, sub-module **208** is configured to correct the areas identified, by data item Y_pwa, as being outside the main statistics, that is, as areas comprising one or a plurality of bad pixels.

[0098] FIG. **4** is an example of the architecture of processing sub-module **204** according to an embodiment of the present disclosure.

[0099] As an example, sub-module **204** comprises a plurality of sub-networks **400**. As an example, sub-module **204** comprises a number Nd, Nd being an integer greater than 2, preferably greater than or equal to 5 and smaller than or equal to 12, of sub-networks **400**.

[0100] As an example, each sub-network **400** is configured to receive input image Y_in and to generate, each, an intermediate data item Y_tmpi. The Nd intermediate data items Y_tmpi are then concatenated, for example in the axis of the channels or in an additional axis.

[0101] Each sub-network **400** comprises, for example, a plurality of layers. As an example, input image Y_in is supplied to a convolutional layer **402** (F–CONV K×K). As an example, layer **402** is a two-dimensional convolutional layer with F output channels, F being an integer greater than or equal to the number of pixels in the mosaic pattern, and comprising kernels of K×K size, where K is an integer greater than the width and/or height of the mosaic pattern.

[0102] As an example, the output generated by layer **402** is supplied to a layer **404** (MOSAIC2CHANNEL). As an example, layer **404** is a so-called pixel shuffle layer, configured to spatially rearrange the channels from close to close to the data item supplied thereto. In particular, layer **404** is configured to perform a so-called "space-to-depth" operation. Further, the performed operation is parameterized by the size of the considered mosaic pattern.

[0103] As an example, the output generated by layer **404** is supplied to a layer **406** (DW CONV 1×1). As an example, layer **406** is a depthwise convolutional layer comprising kernels of 1×1 size, thus allowing an independent weighting of each channel.

[0104] As an example, the output generated by layer **406** is supplied to a layer **408** (MOSAIC2CHANNEL). As an example, layer **408** is a pixel shuffle layer, for example similar to layer **404**.

[0105] As an example, the output generated by layer **408** is supplied to a layer **410** (DW CONV K×K). As an example, layer **410** is a depthwise convolutional layer comprising kernels of K×K size.

[0106] As an example, the output generated by layer **410** is supplied to a layer **412** (MOSAIC2CHANNEL). As an example, layer **412** is a pixel shuffle layer, for example similar to layers **404** and **408**.

[0107] As an example, the output generated by layer **412** is supplied to a layer **414** (DW CONV 1×1) similar to layer **406**.

[0108] As an example, the output generated by layer **414** is supplied to a so-called pixel shuffle layer **416** (CHANNEL2MOSAIC). In particular, layer **416** is configured to perform a so-called "depth-to-space" operation. Further, the operation performed is parameterized by the size of the concerned mosaic pattern.

[0109] As an example, the output generated by layer **416** is supplied to a layer **418** (1–CONV K×K). As an example, layer **418** is a two-dimensional convolutional layer with a single output channel and comprising kernels of K×K size.

[0110] As an example, a concatenation pooling layer **420** (CONCAT) is configured to perform a concatenation of the output data of layers **418** and **408**. As an example, the output data from layer **408** is supplied to layer **420** via a so-called "skip connection". The connection is then configured to supply, for example, ¾ of the output channels from layer **408** directly to layer **420**.

[0111] The concatenation generated by layer **420** is for example supplied to a convolutional layer **422** (3–CONV K×K). As an example, layer **422** is a two-dimensional convolutional layer with three output channels and comprising kernels of K×K size. As an example, the three output channels are the three RGB color channels. Layer **422** is then configured to generate output data item Y_tmpi, corresponding to, for example, a first demosaicing and reconstruction of the input image.

[0112] As an example, data item Y_pwa is injected into the model of network **206** to calculate all or part of intermediate data item Y_tmp.

[0113] According to an embodiment, the parameters of the sub-networks **400** are learned during the training of network **202** described in relation with FIG. **2**.

[0114] FIG. **5** is an example of architecture of attention module **206**, according to an embodiment of the present disclosure.

[0115] Sub-module **206** having the task of detecting, pixel by pixel, bad pixels, an architecture used for image segmentation is adequate for the implementation of sub-module **206**.

[0116] As an example, sub-module **206** then comprises a network **500** (U-NET) of U-net type. In other examples, network **500** is a type of network other than U-net configured to perform image-to-image operations. As an example, network **500** is a variant and/or an improvement of a network of U-net type. As an example, network **500** is further configured to implement internal attention mechanisms and/or to manipulate 2- or 3-dimensional data. As an example, network **500** further comprises a dense interconnection structure.

[0117] As an example, network **500** is a U-net network having a typical depth equal to 4 and comprising receptive field 5×5 convolution blocks with a ReLU-type activation. In an example, network **500** of U-net type is based on convolution blocks comprising two 3×3 convolutions per group, each followed by a channel shuffle. This example is specific and enables to limit the complexity of network **500** and to apply receptive 5×5 fields. Those skilled in the art will be capable of adapting and modulating the sizes of the receptive fields as well as the number of convolution groups. As an example, network **500** is also configured to further perform an subsampling operation, such as a so-called stride operation, for example implemented by a so-called Max-Pooling layer. As an example, the subsampling is an sub-sampling by **2**, corresponding to a 2×2 MaxPooling operation. As an example, network **500** further comprises normalization stages enabling to limit the impact of the absolute amplitude of the data on inference operations. In another example, when the absolute amplitude of the data is an element taken into account in bad pixel detection, network **500** comprises at least one non-normalized path. Skip connections are implemented by a pooling operation, for example a concatenation. As an example, an oversampling operation is implemented by a convolution having a stride size of 2.

[0118] As an example, network **502** is configured to supply the data item that it generates to a layer **504** (L1 NORM). Layer **504** is configured to normalize the received value, for example by application of a normalization performed along the channel axis and noted NL1. The application of normalization NL1 enables the sum of the Nd intermediate data to be equal to 1. As an example, the application of normalization NL1 is performed via a softmax or softargmax-type activation function. Indeed, the softargmax(•) function is equal to NL1(exp(•)). The argmax function thus also returns an output, having the sum of its elements equal to 1. Thus, the various reconstructions of intermediate data item Y_tmp are summed in normalized fashion. As an example, layer **504** is configured to receive a data item having the form of a tensor $T \in \mathbb{R}^{I \times J \times C}$, I and J being, respectively, the number of rows and of columns of pixels in the image and C being the number of channels in the tensor. As an example, for module **204**, values C and Nd are equal. By noting the value of tensor T at position [i,j] in the image and for a channel c, T[i,j,c], layer **504** is for example configured to normalize, for each position, the tensor performing the transformation:

$$NL1(T[i,j,c]) = T[i,j,c] \Big/ \sum_{c=1}^{C} |T[i,j,c]|. \qquad \text{[Math 1]}$$

Further, normalization NL1 is applied to positive data, derived from an activation function of network **500**.

[0119] In another example, to avoid a potential division by 0, the norm L1 of the tensor at position [i,j] is defined as

$$NL1(T[i,j,c]) = T[i,j,c] \Big/ \left(\sum_{c=1}^{C} |T[i,j,c]| + \varepsilon \right), \qquad \text{[Math 2]}$$

where ε is a real number, greater than 0.

[0120] In still another example, the normalization NL1 of the tensor at position [i,j] is defined as NL1(T[i, j, c])=0 or NL1(T[i, j, c])=1/C, if $\Sigma_{c=1}^{C}$|T[i, j, c]|<ε and NL1(T[i, j, c])=T[i, j, c]/$\Sigma_{c=1}^{C}$|T[i, j, c] | otherwise.

[0121] As an example, the output data item Y_pwa of module **206** then corresponds to normalization NL1, defined according to one of the above examples, of the tensor at the output of segmentation network **500**.

[0122] FIG. **6** is an example of the architecture of refinement network **508**, according to an embodiment of the present disclosure.

[0123] As described in relation with FIGS. **2** and **3**, sub-module **208** is configured to generate output Y_pred, during the training of network **202**, or Y_out during the execution of the trained network **202**. The input data are then used to infer the output data item. Data item Y_pwa is, for example, used to select the outputs Y_tmpi of the sub-networks **600**. Data item Y_pwa is for example further used to indicate the type of processing, for example a gating, to be performed on the data item Y_tmp resulting from the first demosaicing and reconstruction performed by sub-module **204**.

[0124] As an example, sub-module **208** comprises a layer **600** (MULT) configured to perform an operation of multiplication, for example pointwise, of tensor Y_tmp based on the values of attention tensor Y_pwa. In another example, layer **600** is configured to perform an operation of multiplexing of tensor Y_tmp based on the values of attention tensor Y_pwa. In the example where layer **600** is configured to perform a multiplexing operation, an activation function of module **206** is of argmax type. The output of layer **600** then is, for example, supplied to a dense layer **602**. Dense layer **602** is then configured to generate an output Y_1 based on the data item supplied by layer **600**. As an example, output Y_1 corresponds to a list of D linear combinations of the outputs of layer **600**, thus generating a tensor of size $W \times H \times N_c \times D$, where W is the pixel width of the image, H the pixel height of the image, and where Nc refers, for example, to the three color channels and where D is the dimension along axis **4** of the tensor. The value of D depends, for example, on the topology as well as on the hyperparameters of network **202**.

[0125] Sub-module **208** further comprises a convolutional layer **604** (CONV 2D) configured to perform a convolution operation on tensor Y_pwa. The result of layer **604** is then supplied to a layer **606** (HARDSIGMOID). As an example, layer **606** is configured to apply an activation function, such as a HardSigmoid function, to the received data item.

[0126] Layer **606** is then configured to supply its output to a layer **608** (RESHAPE). For example, layer **608** is configured to resize the data item supplied by layer **606** into a tensor Y_2 of size W×H×Nc×D.

[0127] As an example, tensor Y_2 is supplied to a layer **610** (x<−1−x) configured to generate a tensor Y_3 by inverting, with respect to 1, the values of tensor Y_2. Tensor Y_2 and data item Y_1 are further supplied to a layer **612** (MULT) similar to layer **600**. As an example, layer **612** is configured to generate a data item Y_4 based on data Y_1 and Y_2.

[0128] Data item Y_4 is supplied to a layer **616** (CNN-CORR). Layer **616** is, for example, a convolutional layer, or a cascade of convolutional layers, configured to generate a data item Y_5 of the defects detected by means of tensor Y_pwa. Thus, the portions of the input image being detected as requiring correction are smoothed.

[0129] Layer **616** is further configured to supply data item Y_5 to a layer **618** (MULT). Layer **618** is further configured to receive data item Y_3, supplied by layer **610**, and to generate a data item Y_6 by performing an operation similar to that performed by layers **600**, **612**, and **614**.

[0130] Sub-module **208** further comprises a layer **620** (ADD). As an example, layer **620** is an additional pooling layer. Layer **620** is for example configured to receive data item Y_4 and the data item at the output of layer **618** and to add them.

[0131] Sub-module **208** further comprises a layer **622** (CNN-COM) configured to generate output data Y_pred or Y_out based on the output of layer **620**. As an example, layer **622** is a convolutional layer, or a cascade of convolutional layers, configured to shape the output data. As an example, the shaping comprises one or a plurality of rotations and/or colorimetric adjustments and/or smoothing and/or shifting operations, and so on.

[0132] According to an embodiment, the use of the HardSigmoid activation function enables an on/off-type detection of bad pixels and to perform an operation similar to a multiplexing by using multiplicative pooling layers and an additional pooling layer.

[0133] Various embodiments and variants have been described. Those skilled in the art will understand that certain features of these various embodiments and variants may be combined, and other variants will occur to those skilled in the art. In particular, regarding the types of the loss functions combined with the focal loss function, variants are possible. Similarly, the design, as well as the topology, of modules **204**, **206**, and **208** may vary.

[0134] Finally, the practical implementation of the described embodiments and variants is within the abilities of those skilled in the art based on the functional indications given hereabove. In particular, the practical implementation of a desired type of imager is within the abilities of those skilled in the art.

1. Method of training a neural network configured to perform image processing operations, the method comprising:

the generation of a modified image, by a modified data generator, based on a first image, the modified image comprising at least one outlier pixel value with respect to the first image;

the supplying of the modified image to the network;

the generation, by the network, of a corrected image;

the supplying of the corrected image, by the network, and the supplying of an indication of the position of the at least one modified pixel, by the generator, to a computing circuit

the generation of an error value, based on the application of a loss function, by the computing circuit, taking as inputs the first image, the indication, and the corrected image;

the correction of parameters associated with the network by backpropagation of the error in the network.

2. Method according to claim **1**, wherein the generation of the corrected image by the network comprises:

the generation, by a first sub-module, of an intermediate data value based on the modified image, the intermediate data item being an at least partial reconstruction of the first image;

the generation, by a second sub-module of the network, of an attention data item based on one of the intermediate data item and/or of the modified image, the attention data item comprising an estimate of the location of the at least one modified pixel;

the generation of the corrected image, by the first sub-circuit or by a third sub-circuit, based on the intermediate data item and on the indication data item.

3. Method according to claim **2**, wherein the generation of the attention data item comprises the execution of a convolutional neural network configured for image segmentation, based on the intermediate data item and/or on the corrected image.

4. Method according to claim **3**, wherein the convolutional neural network is a U-net type network or a variant of a U-net type network.

5. Method according to claim **3**, wherein the generation of the attention data item further comprises an NL1-type normalization, based on the data item generated by the convolutional neural network.

6. Method according to claim **2**, wherein the generation of the corrected image comprises a multiplexing operation and/or a multiplication operation, for example a pointwise multiplication, based on the attention data item and on the intermediate data item.

7. Method according to claim **1**, wherein the generation of an error value comprises the application of a focal loss function taking, as input data, the modified image, the first image, and the indication of the location of the at least one modified pixel.

8. Method according to claim **7**, wherein the generation of an error value further comprises the application:

of a loss function based on an averaging taking, as input data, the modified image and the first image; and/or

of a regularization function taking, as an input data item, the modified image.

9. Method according to claim **1**, wherein the first image is comprised in a database.

10. Method according to claim **1**, wherein the generation of the modified image comprises, for each pixel:

the determination of whether the pixel is to be modified; and

if the pixel is to be modified, the replacing of the value associated with the pixel by an outlier.

11. Method according to claim **1**, wherein the generation of the modified image, by the modified data generator, is further performed based on a mosaic pattern.

12. Method according to claim **1**, wherein the model of the modified data generator is a neural network model previously trained in modified image generation, and configured for the implementation of so-called "style transfer" techniques.

13. Image processing method comprising:

the capture of an image scene, by an imager of an image processing device, the captured image being an image mosaiced according to a mosaic pattern

the supplying of the mosaiced image to a neural network of the processing device trained according to the training method according to claim **1**; and

the generation of a corrected image, by the network, based on the mosaiced image.

14. Image processing method according to claim **13**, wherein the generation of the corrected image by the network comprises:

the supplying of the mosaiced image to a first sub-module of the network configured to generate an intermediate data item by performing a first demosaicing of the mosaiced image;

the supplying of the intermediate data item to a second sub-module of the network configured to generate an attention data item based on the intermediate data item, the attention data item comprising estimates of the location of dysfunctional pixels of the imager; and

the generation of the corrected image, by a third sub-module, based on the intermediate data item and on the attention data item.

15. Image processing method according to claim **13**, wherein the mosaic pattern corresponds to a mosaic pattern used during the generation of a modified image during the training of the network.

16. Image processing device comprising:

an imager configured to capture image scenes, according to a mosaic pattern;

a neural network trained according to the training method according to claim **1**, configured to generate a corrected image based on the mosaiced image.

17. Image processing device according to claim **16** wherein the imager comprises one or a plurality of dysfunctional pixels.

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