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(54) **METHOD AND SYSTEM FOR LEARNING SPATIO-SPECTRAL FEATURES IN AN IMAGE**

VERFAHREN UND SYSTEM ZUM ERLERNEN VON RÄUMLICH-SPEKTRALEN MERKMALEN IN EINEM BILD

PROCEDE ET SYSTEME D'APPRENTISSAGE DE CARACTERISTIQUES SPATIO-SPECTRALES DANS UNE IMAGE

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Description

Background of the Invention

[0001] Many significant and commercially important uses of modem computer technology relate to images. These include image processing, image analysis and computer vision applications. A challenge in the utilization of computers to accurately and correctly perform operations relating to images is the development of algorithms that truly reflect and represent physical phenomena occurring in the visual world. For example, the ability of a computer to correctly and accurately distinguish between a shadow and a material object within an image has been a persistent challenge to scientists. Such an ability can be particularly critical, for example, in computer vision applications, as may be implemented in a robot or a security camera used to identify objects moving through a selected field of view. A computer must be able to identify structures and features of a scene that can be modified in appearance due to overlying shadows. Cognitive processing of the human brain makes it possible for humans to automatically distinguish shadow from object. However, to a computer, it is all pixel values of varying color characteristics. Accordingly, there is a persistent need for the development of accurate and correct techniques that can be utilized in the operation of computers relating to images.

[0002] The document by BARNARD K. et al: "Shadow Identification Using Color Ratios"; 1st Color Imaging Conference, Color Science, Systems and Applications"; 1. January 2000, pages 97-100 (XP003018771) discloses the assessment of illumination boundaries in an image. In order to provide a system which is able to assess the illumination boundaries, a set of roughly 100 measurements of indoor and outdoor illuminations are taken. From these measurements ratios are precomputed, independently of the image to be assessed. The ratios are then used as one ingredient to the assessment of an image.

[0003] The article "Color Feature Detection and Classification by Learning" by Gevers T. et al, Proc. IEEE Conf. on Image Processing (ICIP'05), Vol. 2, pp. 714-717, 2005 describes a method to distinguish material from illumination boundaries using a learning technique. The learning technique utilizes derivatives and curvature of color values in the image.

[0004] The article "Multiple Light Sources and Reflectance Property Estimation based on a Mixture of Spherical Distributions" by Hara K et al, Proc. IEEE Conf. on Computer Vision (ICCV'05), vol. 2, pp. 1627-1634, 2005 describes a method for simultaneously estimating the illumination of the scene and the reflectance property of an object from a single image, under the assumption that the shape of the object is known.

[0005] The article "Recovering Intrinsic Images from a Single Image", IEEE Trans. on Pattern Analysis and Machine Intelligence (PAMI), Vol. 27, No. 9, pp. 1459-1472, 2005 by Tappen, M. F. et al. describes a method for obtaining intrinsic images based on color information and a classifier for gray-scale patterns, which involves image derivatives.

Summary of the Invention

[0006] The present invention provides a learning technique used to identify spatio-spectral features of an image that are useful in the detection of illumination and material features of the image.

[0007] In a first exemplary embodiment of the present invention, an automated, computerized method according to claim 1 is provided.

[0008] In a second exemplary embodiment of the present invention, a computer system according to claim 10 is provided. According to a feature of the present invention, the computer system comprises a CPU and a memory storing an image file. The CPU is arranged and configured to execute a routine to perform a computer learning technique to determine spatio-spectral information for the image file, and to utilize the spatio-spectral information to identify material edges.

Brief Description of the Drawings

[0009]

Figure 1 is a block diagram of a computer system arranged and configured to perform operations related to images, including the recording of images.

Figure 2 shows an n X m pixel array image file for an image, as stored in the computer system of figure 1.

Figure 3 shows an image having an X-junction spatio-spectral feature.

Figure 4 is a flow chart for identifying a local spectral ratio using an X-junction spatio-spectral feature of the type depicted in figure 3, according to a feature of the present invention.

Figure 5 is a flow chart for performing a computer learning technique to learn spatio-spectral features, according to a feature of the present invention.

Figure 6 is a graph showing a real shadow cross-section superimposed with a simulated shadow, according to a feature of the present invention.

Figure 7 is a flow chart for identifying material and illumination using ratio matching, according to a feature of the present invention.

Detailed Description of the Preferred Embodiments

[0010] Referring now to the drawings, and initially to figure 1, there is shown a block diagram of a computer system 10 arranged and configured to perform operations related to images. A CPU 12 is coupled to a device such as, for example, a digital camera 14 via, for example, a USB port. The digital camera 14 operates to download images stored locally on the camera 14, to the CPU 12. The CPU 12 stores the downloaded images in a memory 16 as image files 18. The image files 18 can be accessed by the CPU 12 for display on a monitor 20, or for print out on a printer 22.

[0011] Alternatively, the CPU 12 can be implemented as a microprocessor embedded in a device such as, for example, the digital camera 14 or a robot. The CPU 12 can also be equipped with a real time operating system for real time operations related to images, in connection with, for example, a robotic operation or an interactive operation with a user.

[0012] As shown in figure 2, each image file 18 comprises an n X m pixel array. Each pixel, p, is a picture element corresponding to a discrete portion of the overall image. All of the pixels together define the image represented by the image file 18. Each pixel comprises a digital value corresponding to a set of color bands, for example, red, green and blue color components (RGB) of the picture element. The present invention is applicable to any multi-band image, where each band corresponds to a piece of the electro-magnetic spectrum. The pixel array includes n rows of m columns each, starting with the pixel p (1,1) and ending with the pixel p(n, m). When displaying or printing an image, the CPU 12 retrieves the corresponding image file 18 from the memory 16, and operates the monitor 20 or printer 22, as the case may be, as a function of the digital values of the pixels in the image file 18, as is generally known.

[0013] In an image operation, the CPU 12 operates to analyze the RGB values of the pixels of a stored image file 18 to achieve various objectives, such as, for example, to identify spatio-spectral features of the image. Spatio-spectral features comprise conditions that are indicative of an illumination flux illuminating an image at the time the camera 14 recorded the image represented by the image file 18. An example of a spatio-spectral feature is an X-junction. An X-junction is an area of an image where a material edge and an illumination boundary cross one another. An X-junction is an optimal location for an accurate determination of illumination aspects of the image.

[0014] As taught in published U. S. Patent Application Publication No. 2006/0177149 an image comprises two components, material and illumination. Moreover, as further taught in the Application, an illumination flux impinging on a material depicted in an image is a bi-illuminant flux which comprises an ambient illuminant and a direct or incident illuminant. The incident illuminant is light that causes a shadow and is found outside a shadow perimeter. The ambient illuminant is light present on both the bright and dark sides of a shadow, but is more perceptible within the dark region of a shadow.

[0015] Spectra for the incident illuminant and the ambient illuminant of the illumination flux can be different from one another. A spectral shift caused by a shadow, i.e., a decrease of the intensity of the incident illuminant, will be substantially invariant over different materials present in a scene depicted in an image when the scene is illuminated by a common illumination flux. Thus, the spectral shift caused by a shadow can be expressed by a spectral ratio of colors across an illumination boundary defined by a shadow on a material. A spectral ratio can be defined in a number of ways such as, for example, BRIGHT/DARK, BRIGHT/(BRIGHT-DARK) and DARK/(BRIGHT-DARK), where BRIGHT is the color on the bright side of the shift and DARK is the color on the dark side. In a preferred embodiment of the present invention, the spectral ratio S = DARK/(BRIGHT-DARK) is utilized because it has been discovered during development of the present invention that the normalized value for the ratio DARK/(BRIGHT-DARK) is invariant across different geometric orientations for a material object, and thus, the ratio remains constant across illumination boundaries for objects at different orientations. Moreover, the normalized value for the ratio DARK/(BRIGHT-DARK) produced by a fully shadowed pixel and a penumbra pixel will be the same as the normalized value produced by a fully shadowed pixel and a fully lit pixel.

[0016] Inasmuch as an illumination boundary is caused by the interplay between the incident illuminant and the ambient illuminant of the illumination flux, spectral ratios throughout the image that are associated with illumination change (illuminant ratios), should be consistently and approximately equal, regardless of the color of the bright side or the material object characteristics of the boundary. A characteristic spectral ratio for a particular image or scene within an image, is a spectral ratio associated with illumination change caused by a shadow, as occurs in the particular image, and can be used to determine if a particular boundary in a scene is caused by a shadow or an object.

[0017] Figure 3 shows an image having an X-junction, where a material edge and an illumination boundary cross one another. The hypothesis is that A and B are the same material 1, and that D and C are the same material 2, and that B and C are in shadow. In such circumstances, the reflectance ratios between materials 1 and 2 in each of the lit and shadowed areas should be approximately equal to one another. Thus, A/D = B/C. Moreover, the spectral ratios for the illumination boundary extending across the materials 1 and 2 should be approximately equal, or B/(A-B) = C/(D-C). Thus, the geometry of an X-junction provides a set of criteria that can be determined and verified through analysis of an image. Once identified, the spectral ratio information obtained from the X-junction can be applied as the characteristic spectral ratio for the image in operations such as, for example, object recognition.

[0018] Figure 4 is a flow chart for identifying a local spectral ratio using an X-junction spatio-spectral feature of the type depicted in figure 3, according to a feature of the present invention. The CPU 12 is given an image file 18 and X-junction parameters in step 500. The CPU 12 then proceeds to step 502, which comprises the performance of computer learning techniques to recognize the presence of spatio-spectral features, such as, for example, X-junctions, in the image of the subject image file 18.

[0019] Figure 5 is a flow chart for a learning technique classification procedure implemented to learn spatio-spectral features of an image (step 502 of figure 4), according to a feature of the present invention. The procedure includes the steps of generating a training set (step 520), extracting local image features corresponding to the spatio-spectral features of interest (step 522), building a classifier from the training set, for use in the learning technique to identify spatio-spectral features in an image file 18 (step 524) and classification of spatio-spectral features of an image by applying the classifier to identify spatio-spectral features in the image file 18 (step 526) .

[0020] In step 520, the CPU 12 operates to generate the training set. The training set comprises a set of examples of images having spatio-spectral features, in our example, X-junctions. The examples of X-junctions are positive examples of the type of features to be identified in images depicted in the image files 18. The training set also includes negative examples, images without X-junction features. For an effective and comprehensive training set, thousands of positive and negative examples are included in the set. The X-junction examples can be obtained from actual images, or by generating synthetic examples of X-junctions. A synthetic example comprises a computer generated image having the features illustrated in figure 3. A training set can include both actual examples and synthetic examples.

[0021] Actual examples are obtained by examining images and marking areas of the images that are formed by a shadow extending across two adjacent materials. An exemplary method for generating synthetic spatio-spectral features such as X-junctions, comprises applying a shadow model with varying penumbra sizes and spectral ratios, in a range that is consistent with empirical observations of natural scenes. The spatial component of the model can be expressed by: $s(x) = g(x) * e(x)$, where $s(x)$ denotes the shadow at spatial coordinate x, $g(x)$ denotes a gaussian blurring function, and $e(x)$ denotes an ideal shadow step edge. The spacial extent of a simulated shadow can be varied as a function of the standard deviation of the $g(x)$ term. Figure 6 is a graph showing a real shadow cross-section superimposed with a simulated shadow (jagged line), according to a feature of the present invention. The simulated shadow of figure 6 is obtained by blurring an ideal step edge with the size of the resulting penumbra varied by an amount consistent with variations of a natural image, and caused by changing the standard deviation of $g(x)$. As shown in figure 6, the simulated shadow matches an observation of a natural image.

[0022] According to a further feature of the present invention, the spectral component of the simulated shadow model is the spectral ratio, S = DARK/(BRIGHT-DARK). Variations for the spectral ratio throughout several real world images are determined and applied to the synthetic examples of X-junctions to provide a realistic set of positive examples. Moreover, additional variations for examples of the training set can include varying material colors at the material border and varying the angle between a shadow border and material.

[0023] Upon collecting examples of images having spatio-spectral features, an examination of characteristics of each example relevant to the spatio-spectral features is undertaken by the CPU 12 (step 522). As noted above, the hypothesis for X-junctions, as illustrated in the example of figure 3, is that the reflectance ratios between the materials 1 and 2 in each of the lit and shadowed areas should be approximately equal to one another. Thus, A/D = B/C. Moreover, the spectral ratios for the illumination boundary extending across the materials 1 and 2 should be approximately equal, or B/(A-B) = C/(D-C). Examples in an effective training set should embody characteristics of the image features to be identified (in our example, X-junctions), that can be readily and accurately determined in an image and that accurately indicate the presence of the spatio-spectral feature of interest.

[0024] Key image characteristics are used as an input to a standard classifier, for example, an Adaboost classifier. The Adaboost classifier, in turn, uses the image characteristics to build a profile of an X-junction appearance, as is known in the art. Adaboost is a term of art indicating "adoptive boosting." The Adaboost classifier is described in "A Decision Theoretic Generalization of On-Line Learning and an Application to Boosting," Journal of Computer and System Sciences 55 (1997), pp. 119-139.

[0025] According to a feature of the present invention, the following characteristics of an X-junction are determined (step 522) for each positive sample in the training set, to provide a feature vector for each positive example:

1. Distance between bright pixels of the X-junction example
2. Absolute difference of average brightness of bright pixels
3. DarkBright for Material 1 r (red channel)
4. Dark/Bright for Material 1 g (green channel)
5. Dark/Bright for Material 1 b (blue channel)
6. Dark/Bright for Material 2 r (red channel)
7. Dark/Bright for Material 2 g (green channel)
8. Dark/Bright for Material 2 b (blue channel)
9. Squared Difference of Reflectance Ratio 2/1 (to compare Dark/Bright) (red channel)
10. Squared Difference of Reflectance Ratio 2/1 (to compare Dark/Bright) (green channel)

11. Squared Difference of Reflectance Ratio 2/1 (to compare Dark/Bright) (blue channel)
12. Squared Difference of Spectral Ratio (to compare 1 and 2) (red channel)
13. Squared Difference of Spectral Ratio (to compare 1 and 2) (green channel)
14. Squared Difference of Spectral Ratio (to compare 1 and 2) (blue channel)
15. Number of inliers for first line fit
16. Number of inliers for second line fit
17. Number of outliers for line fits
18. Variance of tilt angle for fitted planes (a spatial plane is fit for the four regions)
19. Average error of plane fitting
20. Feature 20-31 are the RGB values in the 4 regions (the set {A, B, C, D} in our example, figure 3) defined by an X-junction.

[0026] A classifier is built from a learning framework provided by the feature vectors extracted from the positive samples of the training set (step 524). In our example, an Adaboost classifier is built. The classifier provides a computational decision process based on local image features, as represented by the feature vectors. The Adaboost classifier uses adaptive boosting. Boosting is a classifier that collects information from a set of sub-classifiers or "weak learners". A sub-classifier or "weak learner" has accuracy only slightly better than even chance. A simple linear classifier can be used here.

[0027] As an alternative to the preselected set of thirty one characteristics for a feature vector, a large set of possible features and characteristics is generated, for example, by considering relationships among pixels and blocks of pixels in a spatio-spectral feature such as an X-junction. A Probabilistic Learning Tree is then used to determine the most useful characteristics from the large set of possible features. The selected most useful characteristics are then utilized as a basis, for example, of a feature vector used to build a classifier.

[0028] In order to identify the four main regions of a prospective X-junction (set {A, B, C, D}, the feature vectors provide a basis for feature identification of the prospective X-junction. Thus, either the thirty one characteristics selected above or the output of a Probabilistic Learning Tree, provide accurate indications whether a four region area of an image comprise an X-junction. For example, the ratio of dark to bright is a characteristic that is relevant to a region that is shadowed. Regarding characteristics 15-17, two lines are fit to the edge pixels of each of the positive X-junction examples, for example, using a common robust estimator such as RANSAC. A robust estimator identifies "inliers" of the fit. The inliers are the edge pixels that lie on one of the two lines. The outliers are the edge pixels that do not lie on one of the two lines. The inlier and outlier relationships are relevant to X-junction characteristics.

[0029] For characteristics 18 and 19, a spatial plane is fit to the average intensity of each region of each of the positive examples. The parameters of a spatial plane indicate direction and rate of intensity change in the respective region of the positive X-junction example. If the parameters of a region of a prospective X-junction indicate a zero slope plane, the corresponding region is homogeneous. If all four regions of the prospective X-junction have the same tilt angles, the regions may be in the same penumbra. Thus, the tilt angle characteristics (characteristic 18) can be used to support a conclusion that an area of an image is or is not an X-junction. The average error of a plane fitting (characteristic 19) is also indicative of an X-junction.

[0030] As a simple conceptual example illustrating a linear classifier, consider a two-dimensional feature vector so that all the training features lie in a two dimensional grid. Choose a line that divides the grid so that the line can be used as a classifier, i.e. feature points below the line are classified the same. The line is chosen to best classify the training data which is easy to do since the true classification of the training data is already known.

[0031] A description of how boosting works is given in Richard O. Duda, Peter E. Hart, and David G. Stork, Pattern Classification, John Wiley & Sons, Inc., 2001 (pp. 476-480) and Trevor Hastie, Robert Tibshirani, and Jerome Friedman, The Elements of Statistical Learning, Springer, 2001, (pp. 299-309). The boosting description of the *Pattern Classification* reference can be summarized by the following procedural steps:

- Select a subset n_1 of the n patterns from the training set D to get D_1.
- Create a sub-classifier C_1 with D_1. (C_1 can also be called a weak learner).
- Choose a second training set D_2 such that C_1 classifies half of D_2 wrong. (The idea is that D_2 provides information complementary to D_2.) Create sub-classifier C_2.
- Choose D_3 by choosing the training examples such that C_1 and C_2 do not agree
- Continue process until some threshold of training error is achieved or until there are no more training examples. The final classification is based on votes of the sub-classifiers.

[0032] In step 526, the CPU 12 applies the classifier in an analysis of the image depicted in the subject image file 18. From standard brightness edge boundary segment information for the image, the CPU 12 determines crossing boundaries. At the intersection of each crossing boundary pair located within the image, the CPU 12 performs an analysis of each array of pixels within four regions of the image defined by and surrounding each example of intersecting boundaries. The Adaboost classier is used to determine in each case, whether the respective four region set of pixels exhibits characteristics that match the feature vector framework upon which the classifier was built. If yes, the CPU 12 classifies the intersecting boundaries of a particular case, as an X-j unction.

[0033] Upon identification of the X-junctions present in the subject image file 18, the CPU 12 proceeds to step 504 (figure 4). In step 504 the CPU 12 calculates a spectral ratio for each bright/dark pixel pair in each X-junction, and stores the results in a memory array. In step 506, the CPU 12 executes a mean shift algorithm on the array of spectral ratios. The mean shift algorithm can comprise, for example, an algorithm described in "Mean shift analysis and applications," Comaniciu, D.; Meer, P.; Computer Vision, 1999, The Proceedings of the Seventh IEEE International Conference on; Volume 2, 20-27 September, 1999; Pages 1197-1203. The output of execution of the mean shift algorithm (step 508) is a characteristic spectral ratio for all or a specific local region of the image. The execution of step 506 can include a survey of values for the spectral ratios throughout the image.

[0034] If the spectral ratios calculated over the image by, for example, one of the methods described above, vary by an amount > a threshold variance, a local approach will be implemented for the spectral ratio information used in determining illumination boundaries. That is, the value at a specific X-junction, or a mean or median of a set of nearby X-junctions will be used as the spectral ratio when the CPU 12 determines illumination boundaries in the region of the image near the specific X-junction. If all of the spectral ratios for the entire image vary by less than the threshold variance, a global approach can be used with the same mean shift spectral ratio used in all illumination boundary determinations.

[0035] As discussed above, the characteristic spectral ratio is used to identify illumination boundaries in an image. Figure 7 is a flow chart for identifying material and illumination using ratio matching, according to a feature of the present invention. More specifically, the routine of figure 7 identifies illumination flux comprising an illumination boundary. In step 600, the CPU 12 is given spectral ratio information for an image determined through execution of the routine of figure 4, and standard brightness edge boundary segment information for the image. For each brightness edge segment of the image, in step 602, the CPU 12 traverses the edge by selecting, for example, pixel pairs, each pair comprising a pixel from the bright side of an edge segment and a pixel from the dark side of the edge segment.

[0036] In step 604, for each pair of pixels, the CPU 12 calculates a spectral ratio, S = Dark/(Bright - Dark) and accumulates the S values for all the pairs along the corresponding edge segment. In step 606, the CPU 12 decides if the accumulated set of S values for an edge segment matches the given characteristic spectral ratio information. As discussed above, the given spectral ratio information can be a global value for the image or a local value for the part of the image where the edge segment is located. If there is a match of spectral ratios, the CPU 12 marks the edge segment as an illumination boundary (step 608). If there is no match, the CPU 12 marks the edge as a material edge (step 610).

[0037] In the preceding specification, the invention has been described with reference to specific exemplary embodiments and examples thereof. It will, however, be evident that various modifications and changes may be made thereto without departing from the scope of the invention as set forth in the claims that follow. The specification and drawings are accordingly to be regarded in an illustrative manner rather than a restrictive sense.

Claims

1. An automated, computerized method for determining illumination boundaries between areas with an incident illuminant and areas with only an ambient illuminant in an image, comprising the steps of:

    performing a computer learning technique to identify X-junctions in the image,
    wherein an X-junction is an area of the image where a material edge and an illumination boundary cross one another;
    calculating a spectral ratio, which is a ratio of colors with one component for each color channel in the image, for each bright / dark pixel pair of each X-junction;
    obtaining a characteristic spectral ratio as the output of a mean shift algorithm applied to the spectral ratios calculated in the previous step; and
    utilizing the characteristic spectral ratio to identify a given edge in the image as either an illumination boundary or a material edge, by traversing the edge selecting pixel pairs, each pair comprising a pixel from a bright side of the edge and a pixel from a dark side of the edge, calculating a spectral ratio for each pair, and identifying the edge as an illumination boundary, if the accumulated set of spectral ratios for the edge is approximately equal to the characteristic spectral ratio, and identifying the edge as a material edge otherwise.

2. The method of claim 1 wherein the step of performing a computer learning technique to determine X-junctions for the image is carried out by using a training set.

3. The method of claim 2 wherein the training set comprises positive examples and negative examples.

4. The method of claim 3 wherein the positive examples comprise synthetic examples of X-junctions.

5. The method of claim 3 wherein the training set comprises a feature vector set, the set including a feature vector for each positive example of the training set, each feature vector defined by characteristics of the X-junctions.

6. The method of claim 5 comprising the further step of building a classifier as a function of the feature vector set.

7. The method of claim 6 comprising the further step of using the classifier to identify X-junctions.

8. The method of claim 6 wherein the classifier comprises an Adaboost classifier.

9. The method of claim 5 wherein the characteristics are selected by a Probabilistic Learning Tree.

10. A computer system which comprises:

a CPU; and
a memory storing an image file;
the CPU arranged and configured to execute a routine to perform a computer learning technique to identify X-junctions in the image, wherein an X-junction is an area of the image where a material edge and an illumination boundary cross one another; to calculate a spectral ratio, which is a ratio of colors with one component for each color channel in the image, for each bright / dark pixel pair of each X-junction;
to obtain a characteristic spectral ratio as the output of a mean shift algorithm applied to the spectral ratios calculated in the previous step; and to utilize the characteristic spectral ratio to identify a given edge in the image as either an illumination boundary or a material edge, by traversing the edge selecting pixel pairs, each pair comprising a pixel from a bright side of the edge and a pixel from a dark side of the edge,
calculating a spectral ratio for each pair, and identifying the edge as an illumination boundary,if the accumulated set of spectral ratios for the edge is approximately equal to the characteristic spectral ratio, and identifying the edge as a material edge otherwise.

Patentansprüche

1. Automatisiertes, computergestütztes Verfahren zur Bestimmung von Beleuchtungsgrenzen zwischen Bereichen mit einer Einstrahlungsbeleuchtung und Bereichen mit nur einer Umgebungsbeleuchtung in einem Bild, das folgende Schritte umfasst:

Ausführen einer Computerlerntechnik zur Identifizierung von X-Kreuzungen im Bild, wobei eine X-Kreuzung ein Bereich des Bildes ist, wo ein Materialrand und eine Beleuchtungsgrenze einander kreuzen;
Berechnen einer Spektralquote, die eine Quote von Farben mit einer Komponente für jeden Farbkanal im Bild für jedes Hell/Dunkel-Pixelpaar jeder X-Kreuzung ist;
Ermitteln einer charakteristischen Spektralquote als Ausgang eines Mean-Shift-Algorithmus, der auf die im vorangehenden Schritt berechneten Spektralquoten angewendet wird; und
Nutzen der charakteristischen Spektralquote zum Identifizieren eines gegebenen Randes im Bild als Beleuchtungsgrenze oder Materialgrenze durch Überqueren der Randauswahl-Pixelpaare, wobei jedes Paar ein Pixel von einer hellen Seite des Randes und ein Pixel von einer dunklen Seite des Randes umfasst, Berechnen einer Spektralquote für jedes Paar und Identifizieren des Randes als eine Beleuchtungsgrenze, wenn der akkumulierte Satz von Spektralquoten für den Rand annähernd gleich der charakteristischen Spektralquote ist, und ansonsten Identifizieren des Randes als ein Materialrand.

2. Verfahren gemäß Anspruch 1, wobei der Schritt des Ausführens einer Computerlerntechnik zum Bestimmen von X-Kreuzungen für das Bild durch Nutzung eines Übungssatzes ausgeführt wird.

3. Verfahren gemäß Anspruch 2, wobei der Übungssatz positive Beispiele und negative Beispiele umfasst.

4. Verfahren gemäß Anspruch 3, wobei die positiven Beispiele synthetische Beispiele von X-Kreuzungen umfassen.

5. Verfahren gemäß Anspruch 3, wobei der Übungssatz einen Merkmalsvektorsatz umfasst, wobei der Satz einen Merkmalsvektor für jedes positive Beispiel des Übungssatzes umfasst und jeder Merkmalsvektor durch die Eigenschaften der X-Kreuzungen definiert wird.

6. Verfahren gemäß Anspruch 5, das ferner den Schritt des Aufbaus eines Klassifikators als Funktion des Merkmalsvektorsatzes umfasst.

7. Verfahren gemäß Anspruch 6, das ferner den Schritt des Verwendens des Klassifikators zur Identifizierung von X-Kreuzungen umfasst.

8. Verfahren gemäß Anspruch 6, wobei der Klassifikator einen Adaboost-Klassifikator umfasst.

9. Verfahren gemäß Anspruch 5, wobei die Eigenschaften mittels eines probabilistischen Lernbaumes ausgewählt werden.

10. Computersystem umfassend:

eine CPU; und
einen Speicher zum Speichern einer Bilddatei;
wobei die CPU dazu angeordnet und konfiguriert ist, eine Routine zum Ausführen einer Computerlerntechnik zur Identifizierung von X-Kreuzungen im Bild auszuführen, wobei eine X-Kreuzung ein Bereich des Bildes ist, wo ein Materialrand und eine Beleuchtungsgrenze einander kreuzen; eine Spektralquote zu berechnen, die eine Quote von Farben mit einer Komponente für jeden Farbkanal im Bild für jedes Hell/Dunkel-Pixelpaar jeder X-Kreuzung ist; um eine charakteristische Spektralquote als Ausgang eines Mean-Shift-Algorithmus zu ermitteln, der auf die im vorangehenden Schritt berechneten Spektralquoten angewendet wird; und um die charakteristische Spektralquote zur Identifizierung eines gegebenen Randes im Bild als Beleuchtungsgrenze oder Materialgrenze durch Überqueren der Randauswahl-Pixelpaare zu nutzen, wobei jedes Paar ein Pixel von einer hellen Seite des Randes und ein Pixel von einer dunklen Seite des Randes umfasst; um eine Spektralquote für jedes Paar zu berechnen und den Rand als eine Beleuchtungsgrenze zu identifizieren, wenn der akkumulierte Satz von Spektralquoten für den Rand annähernd gleich der charakteristischen Spektralquote ist, und um ansonsten den Rand als einen Materialrand zu identifizieren.

Revendications

1. Procédé automatisé sur ordinateur pour déterminer les limites d'éclairement entre des zones avec un éclairage incident et des zones avec seulement un éclairage ambiant dans une image, comprenant les étapes suivantes :

    exécution d'une technique d'apprentissage sur ordinateur pour identifier des jonctions X dans l'image, une jonction X étant une zone de l'image où un bord de matériau et une limite d'éclairement se croisent ;
    calcul d'un rapport spectral, qui est le rapport des couleurs avec une composante pour chaque canal de couleur dans l'image, pour chaque paire de pixels clair/foncé de chaque jonction X ;
    obtention d'un rapport spectral caractéristique en sortie d'un algorithme à décalage de moyenne appliqué aux rapports spectraux calculés dans l'étape précédente ; et
    utilisation du rapport spectral caractéristique pour identifier un bord donné dans l'image comme soit une limite d'éclairement, soit un bord de matériau, en traversant les paires de pixel marquant le bord, chaque paire comprenant un pixel d'un côté clair du bord et un pixel d'un côté sombre du bord, en calculant un rapport spectral pour chaque paire et en identifiant le bord comme une limite d'éclairement si l'ensemble cumulé des rapports spectraux pour le bord est approximativement égal au rapport spectral caractéristique, et en identifiant le bord comme un bord de matériau dans le cas contraire.

2. Procédé selon la revendication 1, dans lequel l'étape d'exécution d'une technique d'apprentissage par ordinateur pour déterminer les jonctions X pour l'image est réalisée à l'aide d'un ensemble d'entraînement.

3. Procédé selon la revendication 2, dans lequel l'ensemble d'entraînement comprend des exemples positifs et des exemples négatifs.

4. Procédé selon la revendication 3, dans lequel les exemples positifs comprennent des exemples de synthèse des jonctions X.

5. Procédé selon la revendication 3, dans lequel l'ensemble d'entraînement comprend un ensemble de vecteurs de caractéristiques, l'ensemble comprenant un vecteur de caractéristiques pour chaque exemple positif de l'ensemble d'entraînement, chaque vecteur de caractéristiques étant défini par des caractéristiques des jonctions X.

6. Procédé selon la revendication 5, comprenant l'étape supplémentaire de constitution d'un classificateur en fonction de l'ensemble de vecteurs de caractéristiques.

7. Procédé selon la revendication 6 comprenant l'étape supplémentaire d'utilisation du classificateur pour identifier les jonctions X.

8. Procédé selon la revendication 6, dans lequel le classificateur comprend un classificateur AdaBoost.

9. Procédé selon la revendication 5, dans lequel les caractéristiques sont sélectionnées par un arbre d'apprentissage probabiliste.

10. Système d'ordinateur comprenant :

    une unité centrale à processeur et
    une mémoire stockant un fichier d'image,
    l'unité centrale à processeur étant disposée et configurée pour appliquer une routine afin d'exécuter une technique d'apprentissage par ordinateur pour identifier des jonctions X dans l'image, une jonction X étant une zone de l'image où un bord de matériau et une limite d'éclairement se croisent ;
    pour calculer un rapport spectral qui est le rap-

port des couleurs avec une composante pour chaque canal de couleur dans l'image, pour chaque paire de pixels clair/foncé de chaque jonction X ;

pour obtenir un rapport spectral caractéristique en sortie d'un algorithme à décalage de moyenne appliqué aux rapports spectraux calculés dans l'étape précédente ; et

pour utiliser le rapport spectral caractéristique pour identifier un bord donné dans l'image comme soit une limite d'éclairement, soit un bord de matériau, en traversant les paires de pixel marquant le bord, chaque paire comprenant un pixel d'un côté clair du bord et un pixel d'un côté sombre du bord, en calculant un rapport spectral pour chaque paire et en identifiant le bord comme une limite d'éclairement si l'ensemble cumulé des rapports spectraux pour le bord est approximativement égal au rapport spectral caractéristique, et en identifiant le bord comme un bord de matériau dans le cas contraire.

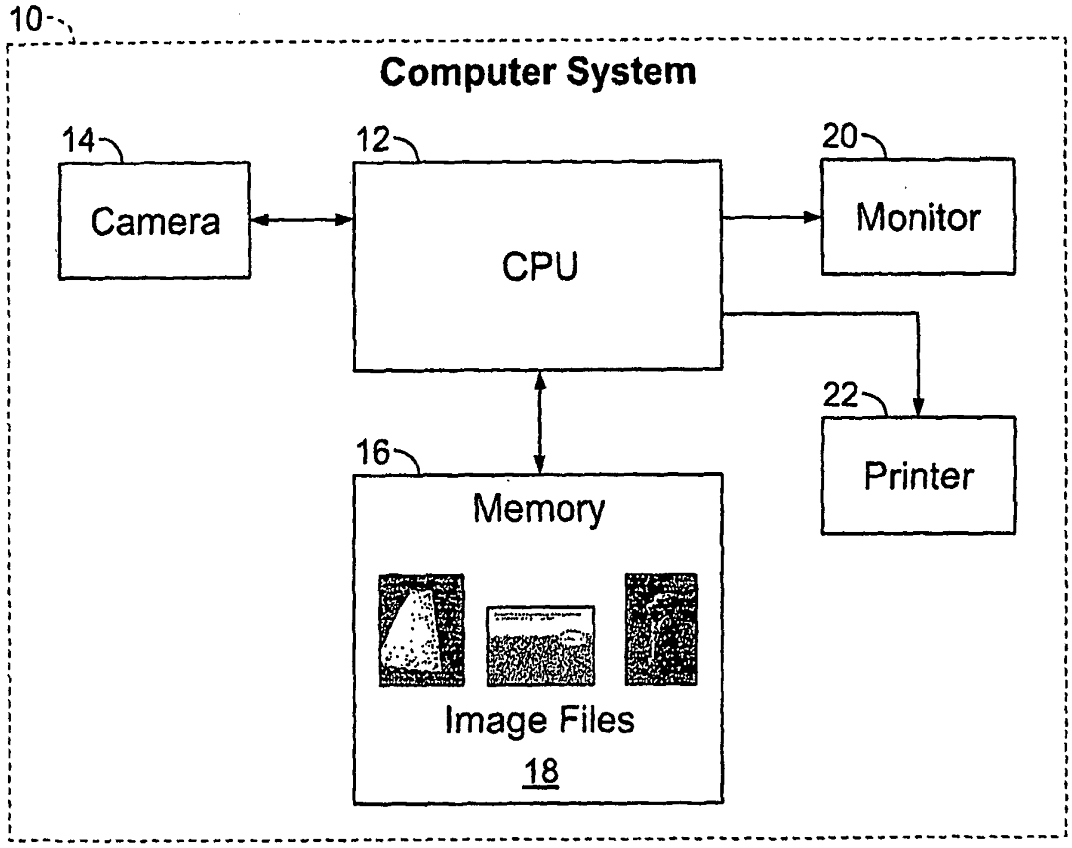
10
Computer System
14
Camera
12
CPU
20
Monitor
22
Printer
16
Memory
Image Files
18

FIG. 1

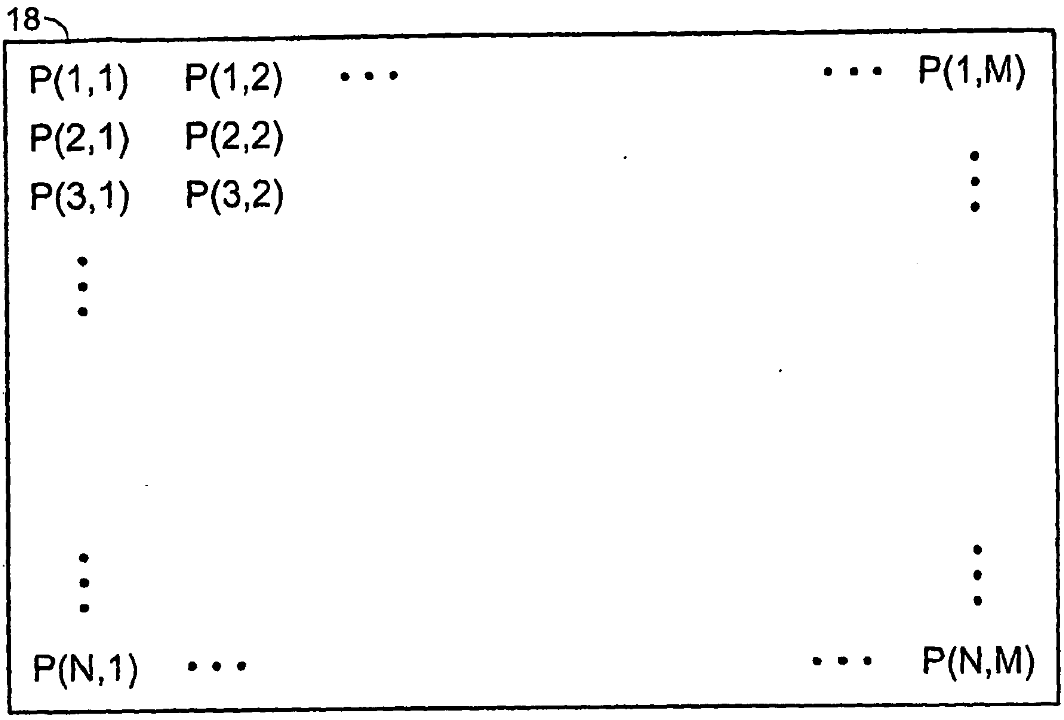
18
P(1,1)
P(1,2)
P(1,M)
P(2,1)
P(2,2)
P(3,1)
P(3,2)
P(N,1)
P(N,M)

FIG. 2

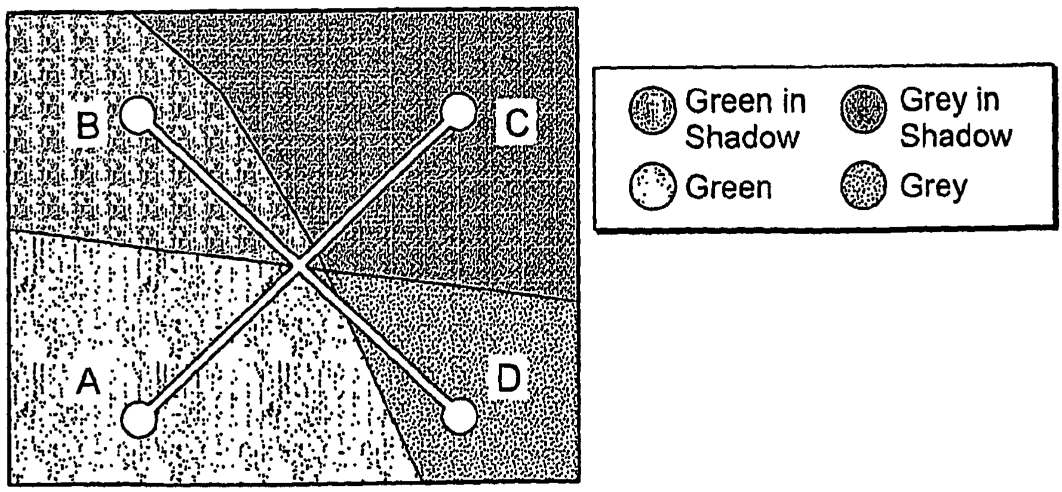
B
C
A
D
Green in Shadow
Grey in Shadow
Green
Grey

FIG. 3

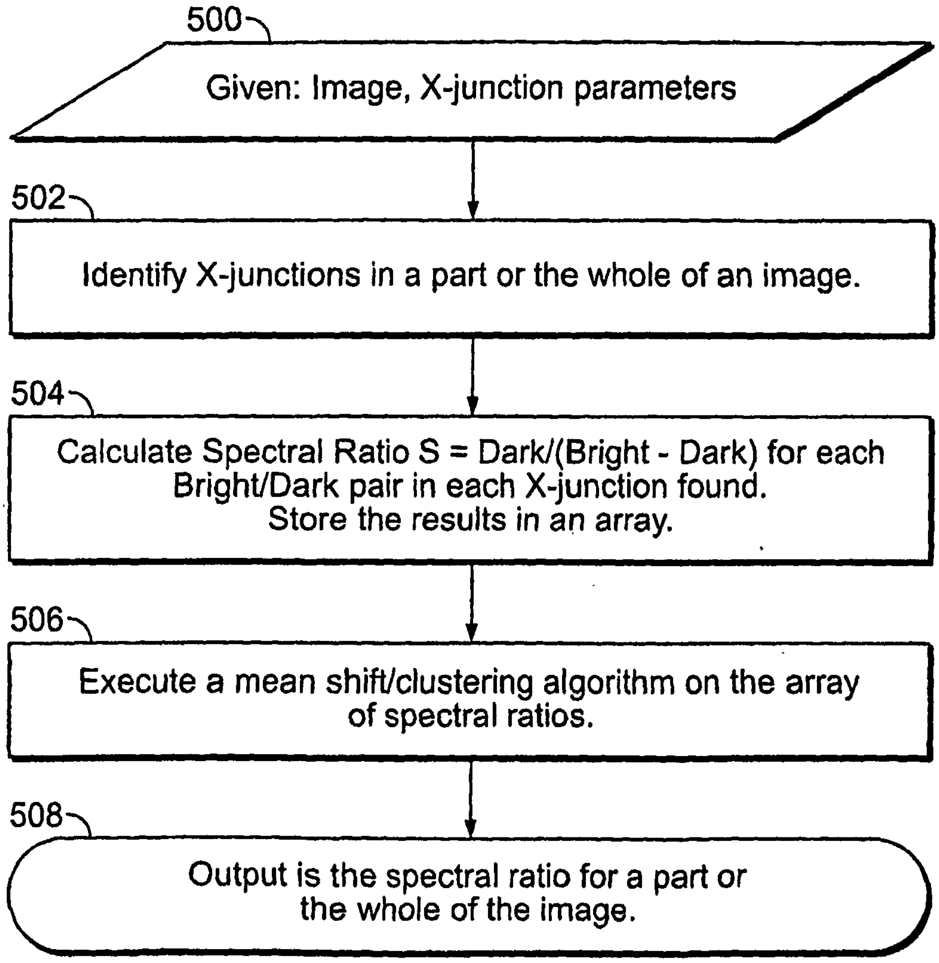
500
Given: Image, X-junction parameters
502
Identify X-junctions in a part or the whole of an image.
504
Calculate Spectral Ratio S = Dark/(Bright - Dark) for each Bright/Dark pair in each X-junction found. Store the results in an array.
506
Execute a mean shift/clustering algorithm on the array of spectral ratios.
508
Output is the spectral ratio for a part or the whole of the image.

FIG. 4

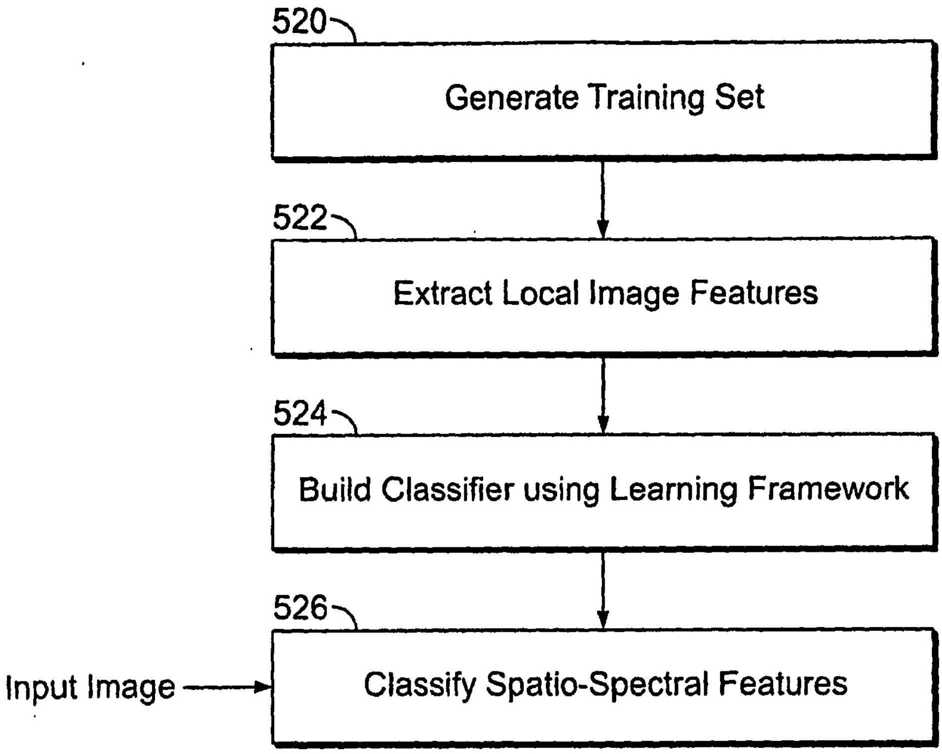
520
Generate Training Set
522
Extract Local Image Features
524
Build Classifier using Learning Framework
526
Input Image
Classify Spatio-Spectral Features

FIG. 5

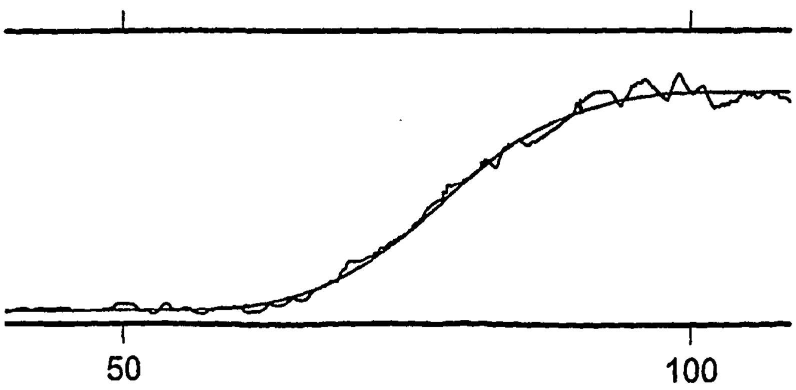
50
100

FIG. 6

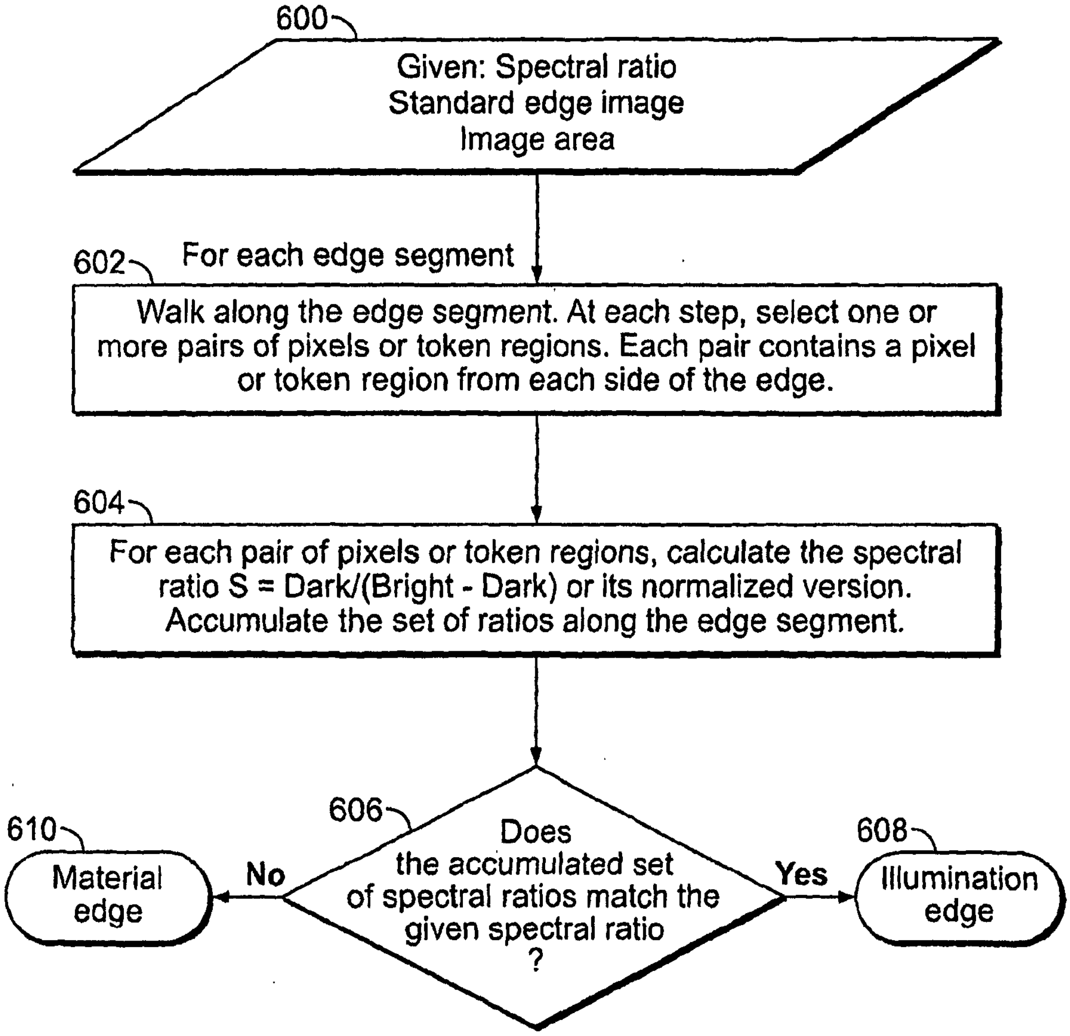
600
Given: Spectral ratio
Standard edge image
Image area
602
For each edge segment
Walk along the edge segment. At each step, select one or more pairs of pixels or token regions. Each pair contains a pixel or token region from each side of the edge.
604
For each pair of pixels or token regions, calculate the spectral ratio S = Dark/(Bright - Dark) or its normalized version. Accumulate the set of ratios along the edge segment.
606
Does the accumulated set of spectral ratios match the given spectral ratio ?
No
Yes
610
Material edge
608
Illumination edge

FIG. 7

REFERENCES CITED IN THE DESCRIPTION

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