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Rephaeli et al.

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(54) **OPTICAL IMPLEMENTATION OF MACHINE LEARNING FOR REAL TIME INCREASED CONTRAST VIA MULTIPLE WAVELENGTH ILLUMINATION WITH TUNABLE POWER**

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(Continued)

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G01J 3/10 (2006.01)
(Continued)

(52) **U.S. Cl.**
CPC ***G06K 9/2027*** (2013.01); ***G01J 3/10*** (2013.01); ***G01J 3/2823*** (2013.01);
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(58) **Field of Classification Search**
CPC .. G06K 9/2027; G06K 9/6212; G06K 9/6218; G06K 9/6268; G06K 9/6269;
(Continued)

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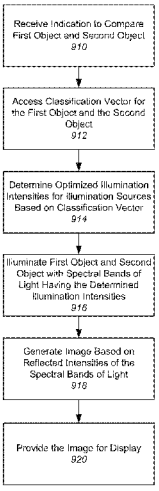
(57) **ABSTRACT**

An imaging system (e.g., hyperspectral imaging system) receives an indication to compare a first object and a second object (e.g., two anatomical structures or organs in a medical environment). The imaging system accesses a classification vector for the first object and the second object, the classification vector having been extracted by separating a plurality of collected reflectance values for the first object from a plurality of collected reflectance values for the second object. A set of optimal illumination intensities for one or more spectral illumination sources of the imaging system is determined based on the extracted classification vector. The first and second objects are illuminated with the determined illumination intensities. A high-contrast image of the first and second objects is provided for display, such that the two objects can be readily distinguished in the image. The intensity of pixels in the image is determined by the illumination intensities.

20 Claims, 10 Drawing Sheets



Related U.S. Application Data

(60) Provisional application No. 62/310,539, filed on Mar. 18, 2016.

(51) **Int. Cl.**

G01J 3/28	(2006.01)
G06K 9/62	(2006.01)
H04N 5/235	(2006.01)
G06K 9/00	(2006.01)
G06K 9/46	(2006.01)

(52) **U.S. Cl.**

CPC ***G06K 9/6212*** (2013.01); ***G06K 9/6218*** (2013.01); ***G06K 9/6268*** (2013.01); ***G06K 9/6269*** (2013.01); ***H04N 5/2354*** (2013.01); *G01J 2003/2826* (2013.01); *G06K 2009/00644* (2013.01); *G06K 2009/4657* (2013.01)

(58) **Field of Classification Search**

CPC .. G06K 2009/00644; G06K 2009/4657; G01J 3/10; G01J 3/2823; G01J 2003/2826; H04N 5/2354

See application file for complete search history.

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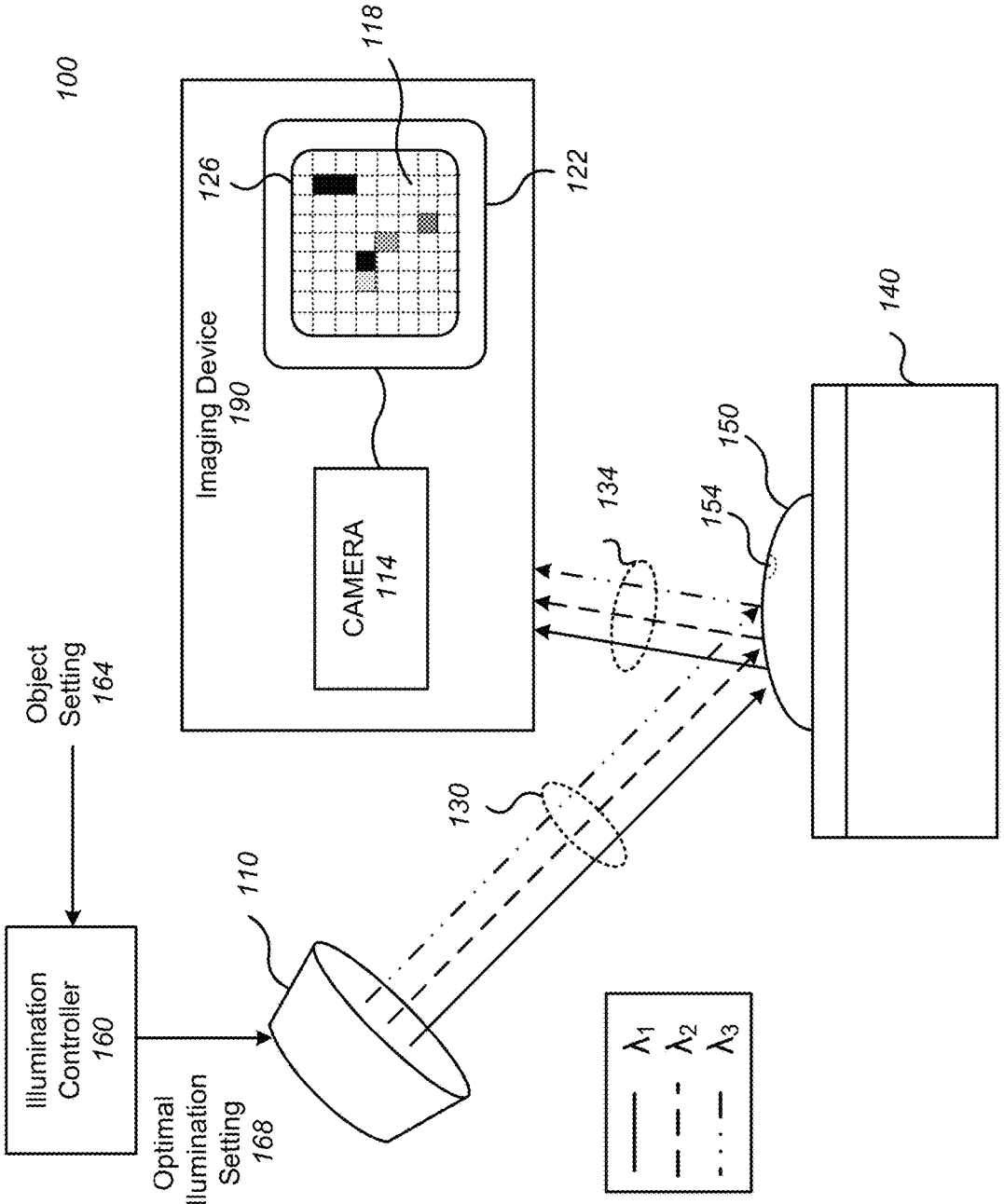
100
118
126
122
Imaging Device
190
CAMERA
114
140
150
134
154
130
110
Object
Setting
164
Illumination
Controller
160
Optimal
Illumination
Setting
168
λ1
λ2
λ3

FIG. 1

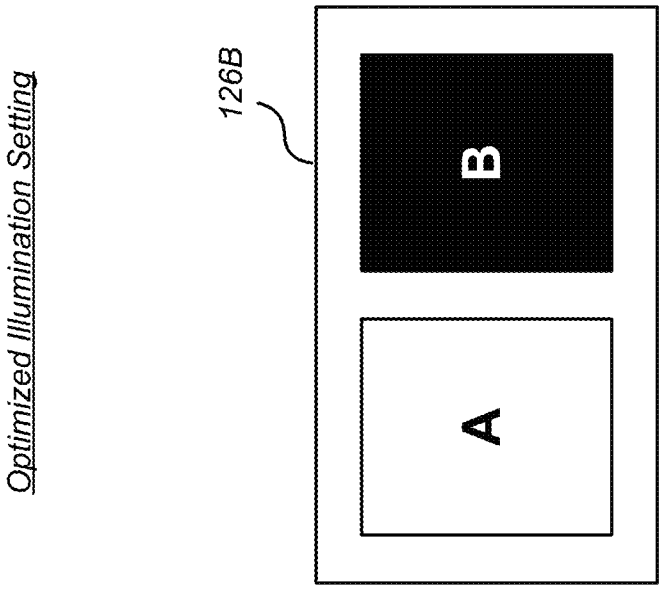
Optimized Illumination Setting
126B
B
A

FIG. 2B

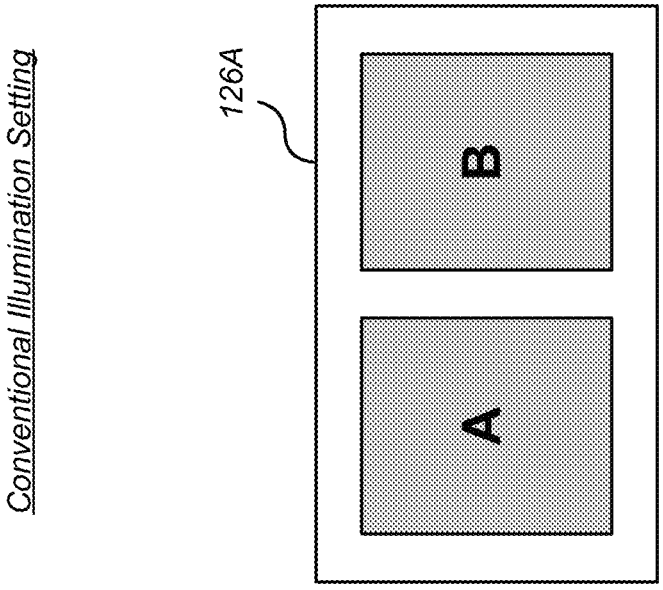
Conventional Illumination Setting
126A
B
A

FIG. 2A

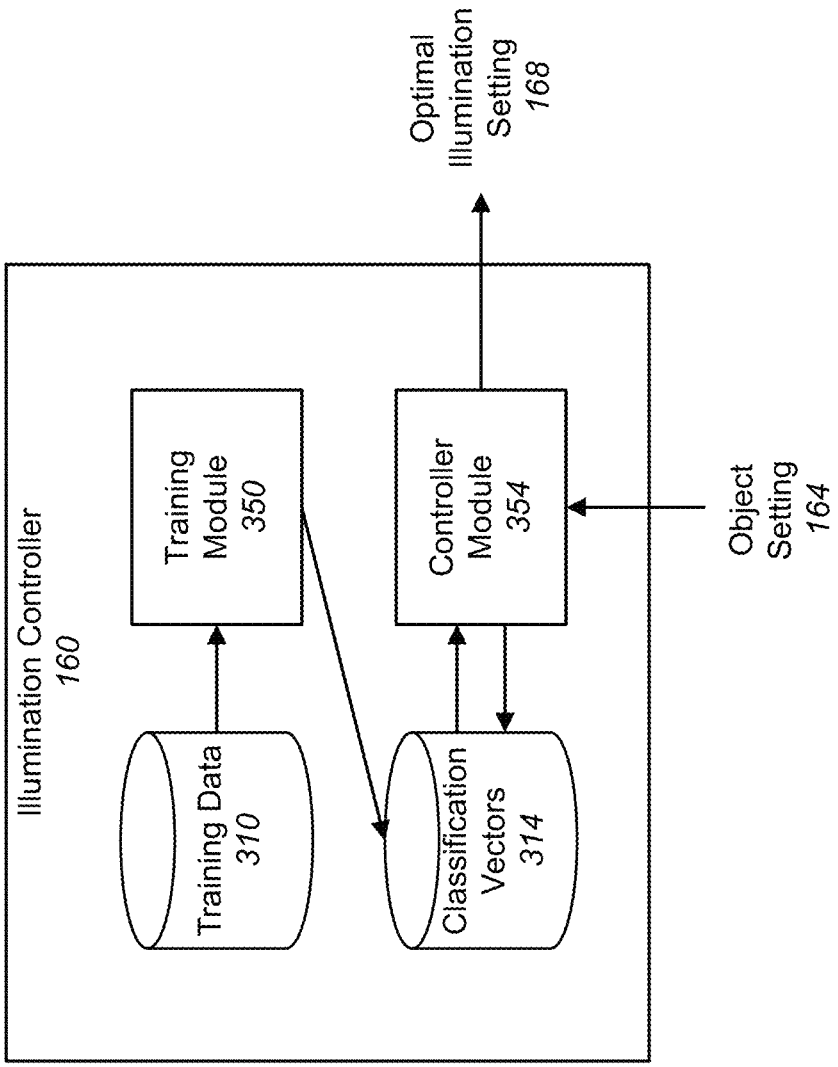
Optimal Illumination Setting 168
Illumination Controller 160
Training Module 350
Controller Module 354
Object Setting 164
Training Data 310
Classification Vectors 314

FIG. 3

Training Data
310

Entry #	$R(\lambda_1)$	$R(\lambda_2)$	$R(\lambda_3)$	...	$R(\lambda_n)$	Object
1	0.8	0.21	0.01		0.58	A
2	0.69	0.02	0.03		0.03	A
3	0.01	0.45	0.03		0.78	A
4	0.58	0.65	0.06		0.95	A
5	0.28	0.36	0.58		0.36	B
6	0.32	0.56	0.47		0.48	B
7	0.4	0.98	0.45		0.47	A
8	0.09	0.87	0.69		0.68	A

X_{train} y_{train}

FIG. 4

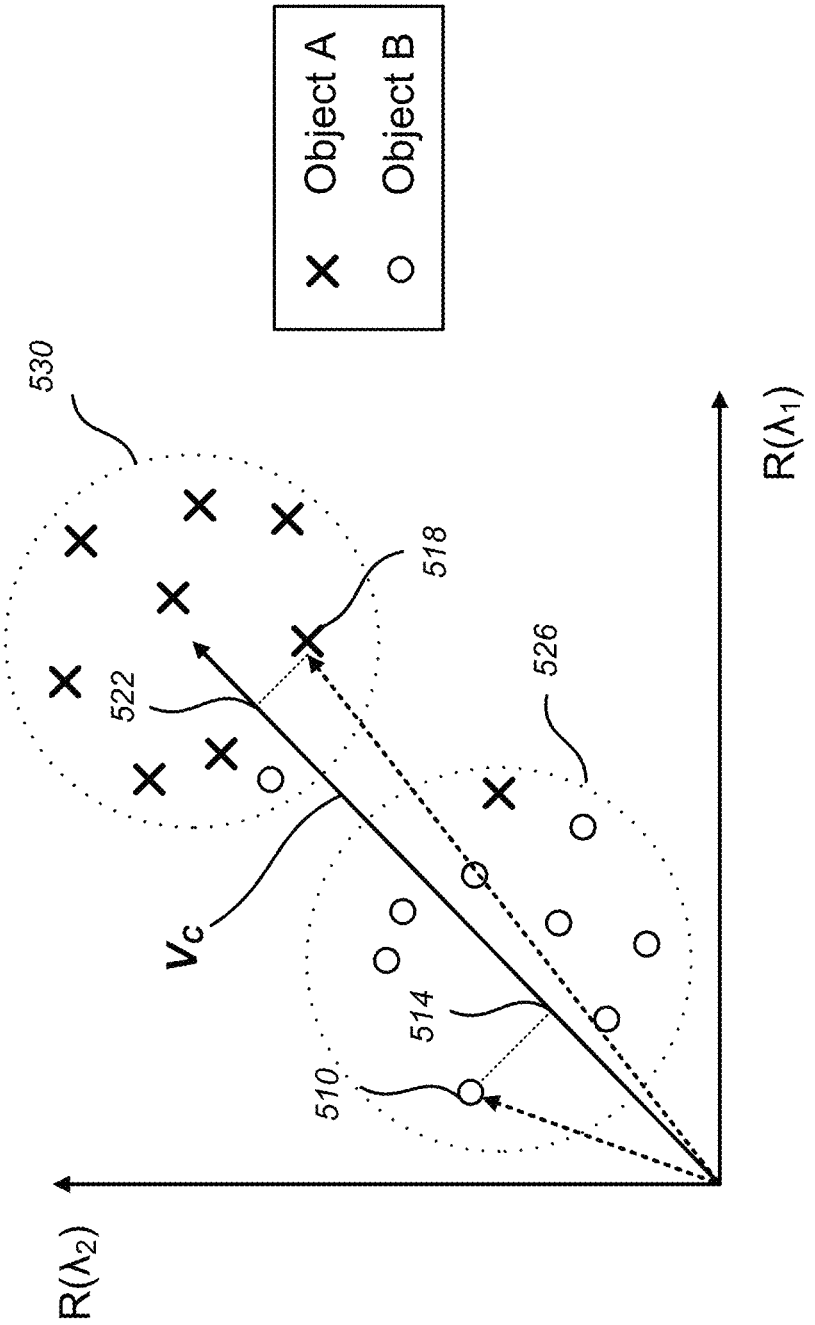
Object A
Object B
530
518
522
526
514
510
V_C
$R(\lambda_1)$
$R(\lambda_2)$

FIG. 5

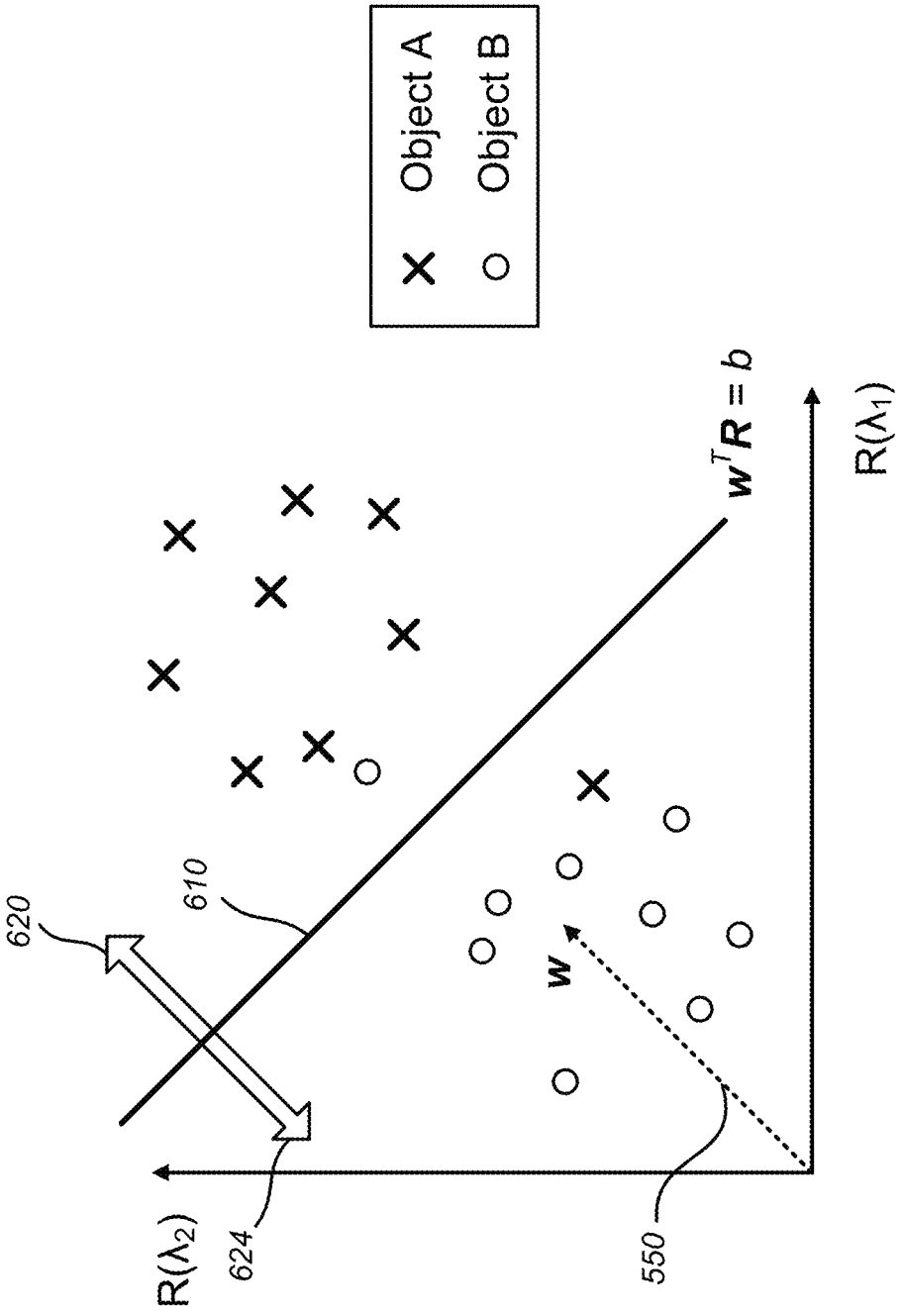

FIG. 6

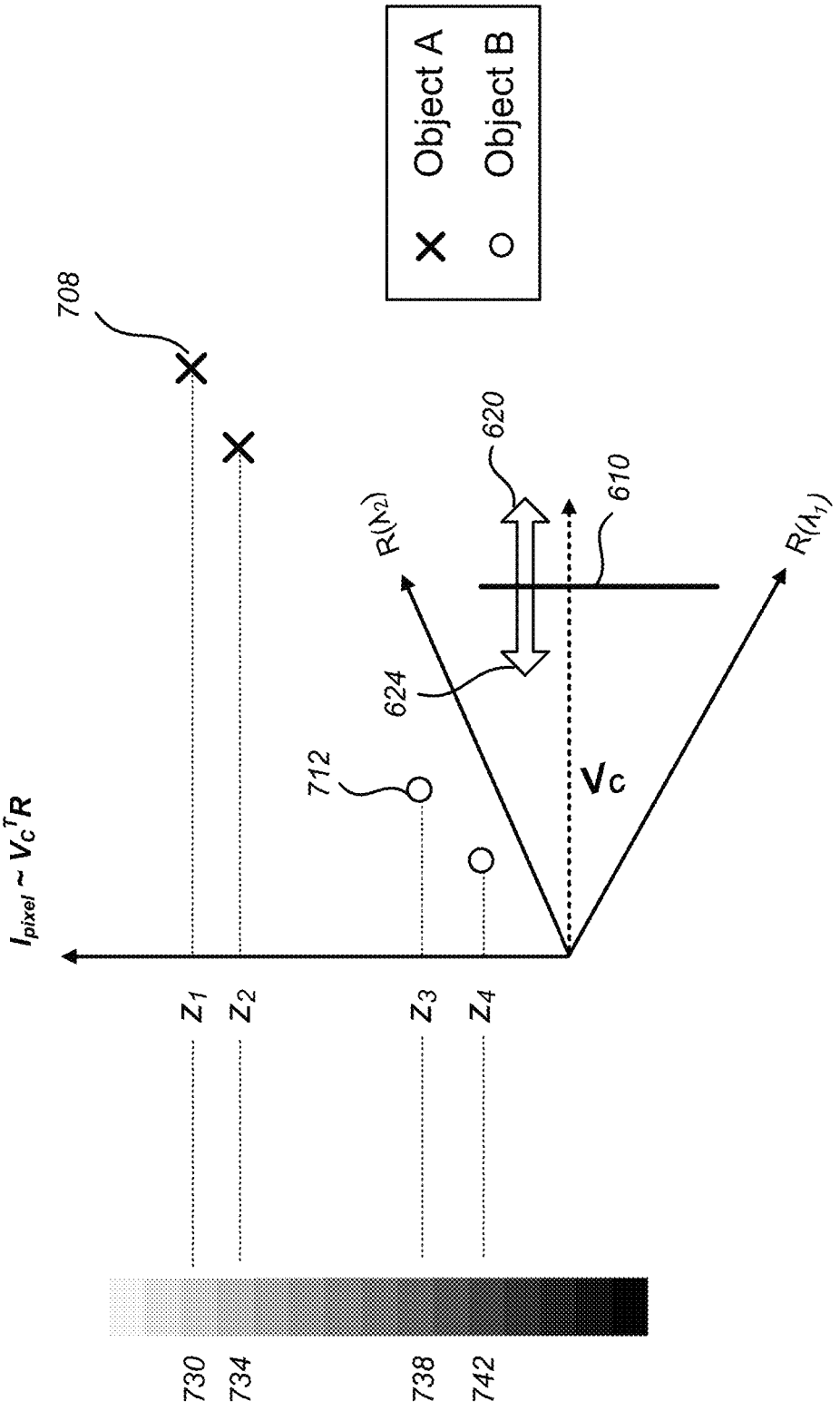
Object A
Object B
708
620
610
$R(\lambda_2)$
$R(\lambda_1)$
624
712
V_C
$I_{pixel} \sim V_C{}^T R$
z_1
z_2
z_3
z_4
730
734
738
742

FIG. 7

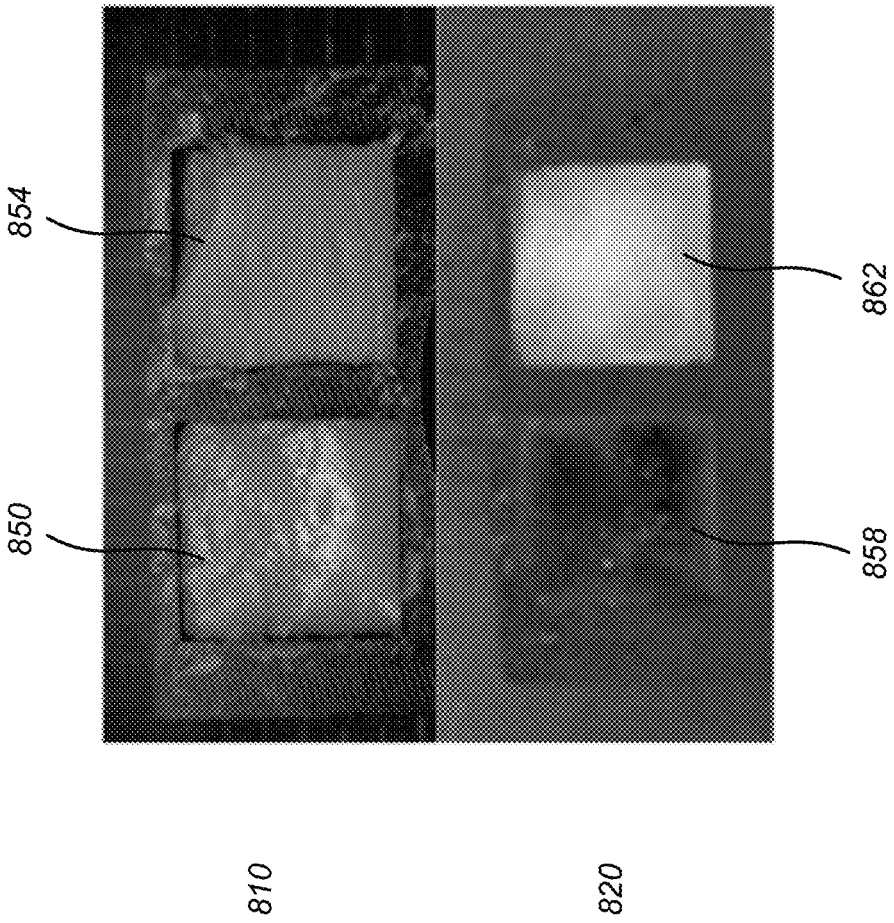

FIG. 8

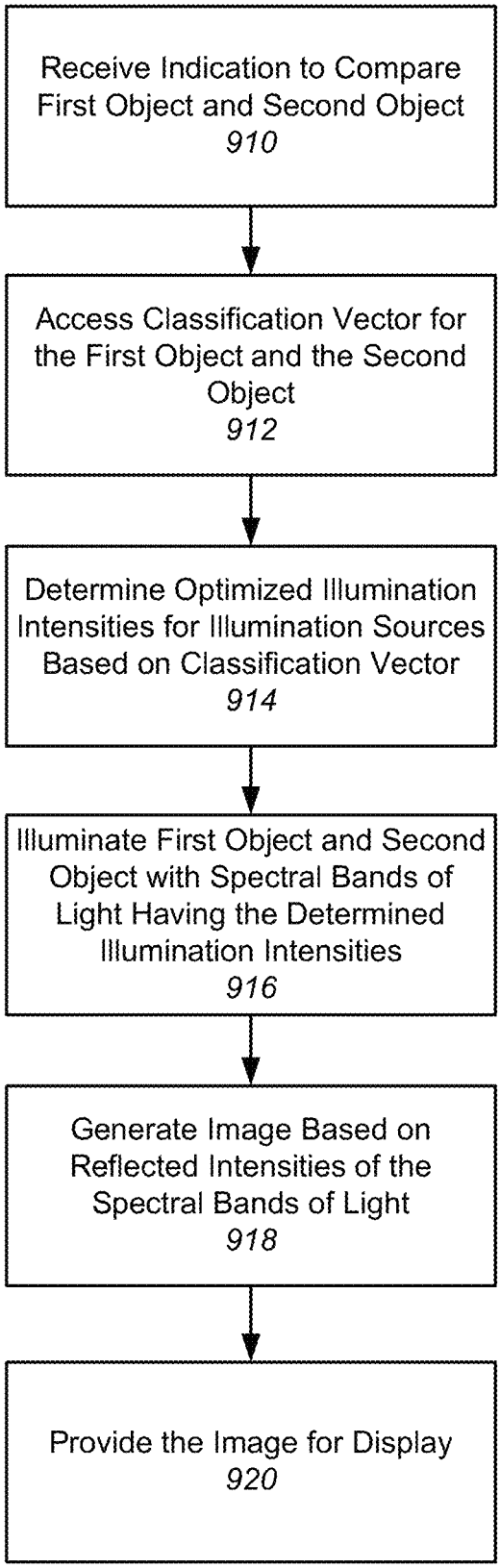
Receive Indication to Compare First Object and Second Object
910
Access Classification Vector for the First Object and the Second Object
912
Determine Optimized Illumination Intensities for Illumination Sources Based on Classification Vector
914
Illuminate First Object and Second Object with Spectral Bands of Light Having the Determined Illumination Intensities
916
Generate Image Based on Reflected Intensities of the Spectral Bands of Light
918
Provide the Image for Display
920

FIG. 9

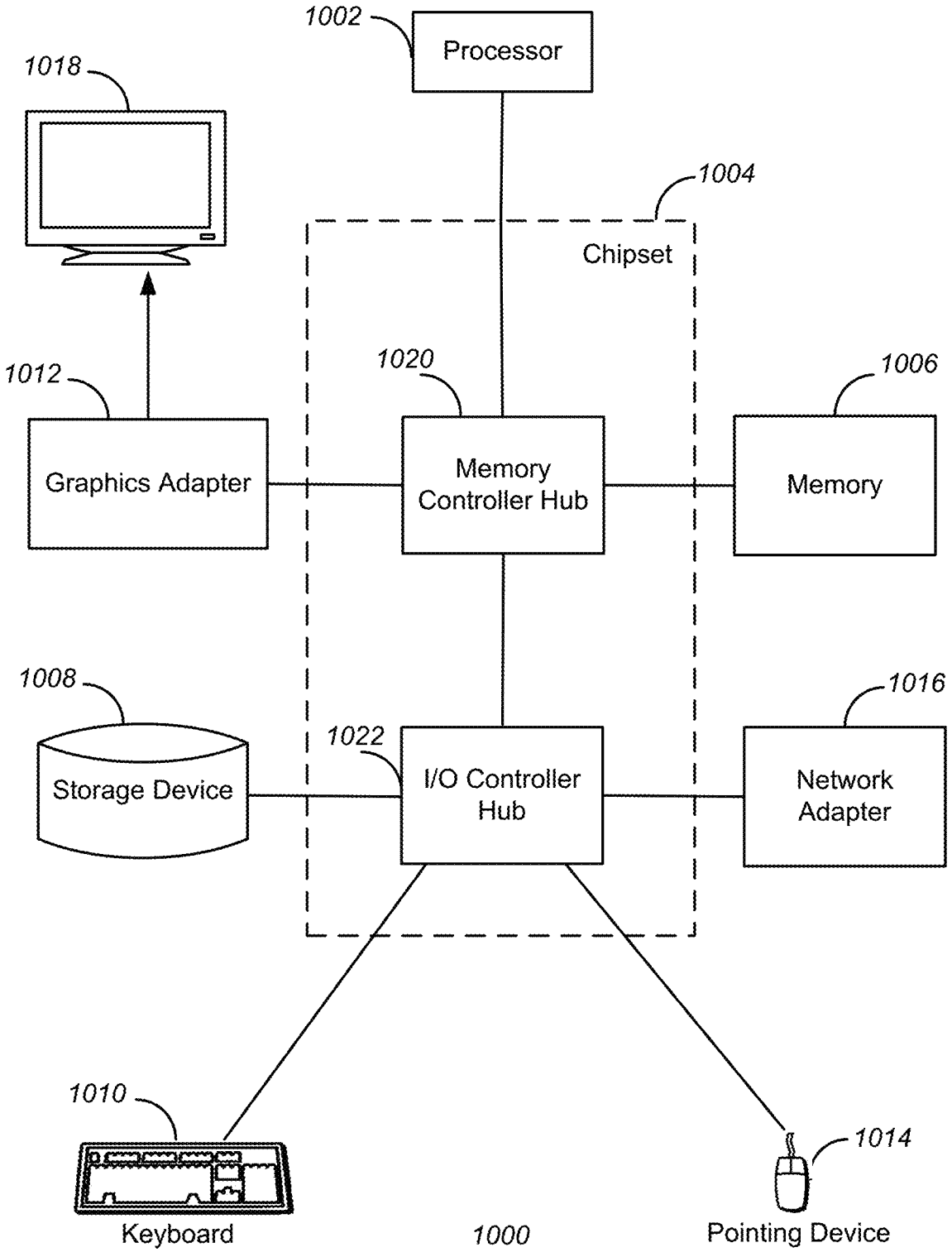
1002
Processor
1018
1004
Chipset
1012
1020
1006
Graphics Adapter
Memory Controller Hub
Memory
1008
1016
1022
Storage Device
I/O Controller Hub
Network Adapter
1010
1014
Keyboard
1000
Pointing Device

FIG. 10

OPTICAL IMPLEMENTATION OF MACHINE LEARNING FOR REAL TIME INCREASED CONTRAST VIA MULTIPLE WAVELENGTH ILLUMINATION WITH TUNABLE POWER

CROSS-REFERENCE TO RELATED APPLICATIONS

The present application is a non-provisional patent application claiming priority to Provisional Patent Application No. 62/310,539, filed Mar. 18, 2016, and Non-Provisional patent application Ser. No. 15/460,927, field Mar. 16, 2017, the contents of which are hereby incorporated by reference.

FIELD OF DISCLOSURE

The present invention generally relates to generating an image with optimized contrast using an imaging system, such as a hyperspectral imaging system.

BACKGROUND

The ability to visually distinguish different objects through imaging is critical for many applications. Oftentimes, the objects to be discerned are different in nature but may appear similar to the naked eye or under a conventional imaging process. For example, in medical imaging and surgical imaging, it is of paramount importance that the surgeon can distinguish between different anatomical structures.

In the conventional process of imaging, the intensity of a pixel in an image sensor is found by physically integrating over the spectral and angular dimensions of the incident spectral illumination. However, since the pixel intensity is found by integrating over the spectral dimensions of the incident light, the conventional imaging process may fail to detect individual spectral components in the incident light that might be able to provide scene-specific or scene-general contrast for distinguishing the objects.

SUMMARY

An imaging system receives an indication to compare a first object and a second object. The imaging system accesses a classification vector for the first object and the second object. The classification vector is extracted by separating a plurality of collected reflectance values for the first object from a plurality of collected reflectance values for the second object. A set of optimal illumination intensities for one or more spectral illumination sources of the imaging system is determined based on the extracted classification vector. The first object and the second object is illuminated with the determined illumination intensities. A high-contrast image of the first object and the second object is provided for display. The intensity of pixels in the image is determined by the illumination intensities.

BRIEF DESCRIPTION OF THE FIGURES

FIG. **1** is an imaging system for displaying an image of an article, according to one embodiment.

FIG. **2**A is an example image generated by a conventional illumination setting, according to one embodiment.

FIG. **2**B is an example image generated by an optimized illumination setting, according to one embodiment.

FIG. **3** is a block diagram illustrating the illumination controller, according to one embodiment.

FIG. **4** illustrates example training data provided to the training module for identifying a classification vector, according to one embodiment.

FIG. **5** illustrates a classification vector V_c for two objects A and B, according to one embodiment.

FIG. **6** is an example classifier trained by the training module, according to one embodiment.

FIG. **7** illustrates the relationship between a pixel intensity I_{pixel} in image, and the projection of the corresponding surface area element reflectance onto the classification vector V_C retrieved from the classifier in FIG. **6**, according to one embodiment.

FIG. **8** shows an un-optimized image of turkey meat and chicken meat under conventional illumination, and an optimized image of the same under optimal illumination.

FIG. **9** is a flowchart illustrating the process of generating an image with optimized contrast between two or more objects A and B using the imaging system of FIG. **1**, according to one embodiment.

FIG. **10** is a block diagram of a computer for implementing the illumination controller, according to one embodiment.

DETAILED DESCRIPTION

The Figures (FIGS.) and the following description describe certain embodiments by way of illustration only. One skilled in the art will readily recognize from the following description that alternative embodiments of the structures and methods illustrated herein may be employed without departing from the principles described herein. Reference will now be made in detail to several embodiments, examples of which are illustrated in the accompanying figures. It is noted that wherever practicable similar or like reference numbers may be used in the figures and may indicate similar or like functionality.

System Overview

FIG. **1** is an imaging system **100** for displaying an image **126** of an article **150**, according to one embodiment. A hyperspectral imaging system will be used as an example of the imaging system **100** throughout the application, though other imaging systems could also be used.

The imaging system **100** includes an illumination source **110**, a table **140** for supporting an article **150**, an imaging device **190**, and an illumination controller **160**. The imaging device **190** may further include a camera **114**, and a monitor **122** for displaying an image **126** of the article **150**, or may be an eye that generates an image **126** of the article **150** in the brain. Some embodiments of the imaging system **100** have different or additional modules than the ones described here. Similarly, the functions can be distributed among the modules in a different manner than is described here. Certain modules and functions can be incorporated into other modules of the imaging system **100**.

The imaging system **100** displays an image **126** with optimized contrast between two or more objects by adjusting the intensities of each spectral band of the illumination source **110**. The article **150** includes two or more objects, such as objects A and B, which are of different nature but are not easily differentiable to the naked eye or to a conventional imaging system. The imaging system **100** displays an image **126**B of the article **150** having an optimized contrast between the image portion of A and the image portion of B. That is, the contrast between objects A and B are enhanced in the image **126**B compared to that of a conventional imaging system or to the naked eye. This optimized contrast between objects can be useful, for example, in a medical or

surgical setting in which a surgeon or other medical personnel must distinguish between two anatomical structures in the body that can appear very similar in a conventional image. The optimized contrast between the anatomical structures instead ensures that these two different structures will clearly stand out to the surgeon as different structures in the image, ensuring that the surgeon is able to readily distinguish the structures during a surgical procedure or in a different medical setting.

FIG. **2**A is an example image **126**A generated by a conventional illumination setting, according to one embodiment. FIG. **2**B is an example image **126**B generated by an optimized illumination setting, according to one embodiment.

As shown in FIG. **2**A, conventional image **126**A shows an image **126** of an article **150** containing two different objects A and B. Although objects A and B may be of different materials or of different nature, the image portion of object A and the image portion of object B have similar intensity under conventional illumination that makes it difficult to differentiate between the two objects. In contrast, as shown in FIG. **2**B, an optimized image **126**B generated by adjusting the intensities of the illumination source **110** shows an image of the same article **150**, in which the image portion of A and the image portion of object B have significantly different intensities that enhance the discernibility between the two objects.

Returning to FIG. **1**, the system **100** illuminates the article **150** with incident light **130** from the illumination source **110** having a combination of light from different spectral bands, detects the intensity of reflected light **134** from the article **150**, and generates an image **126** of the article **150** by analyzing the intensity of reflected light **134** with the imaging device **190**. As an example, the imaging device **190** may refer to a camera **114** that integrates or sums the reflected intensities for each pixel of the image **126** displayed on the monitor **122**. The integrated or summed value is translated into the scale of the pixel for display in image **126**. After receiving an object setting **164** indicating two or more objects A and B to be distinguished, the system **100** adjusts the individual illumination intensities of each spectral band in the incident light **130**, such that the resulting image **126** is of optimized contrast between the portion of object A and the portion of object B. The system **100** adjusts the illumination intensities by analyzing reflectance data associated with other instances of objects A and B.

The illumination source **110** is a light source that can illuminate the article **150** with light from two or more spectral bands, and also adjust the individual intensities of light for each spectral band. In one embodiment, each spectral band may be a narrow-band that has a relatively small spectral range in the wavelength spectrum of light. Each spectral band may be characterized by a wavelength value, even though a spectral band may correspond to a spectral range of light. For example, as shown in FIG. **1**, the illumination source **110** emits incident light **130** having a combination of 3 spectral bands, characterized by λ_1, λ_2, and λ_3, each having a corresponding illumination intensity of $I(\lambda_1)$, $I(\lambda_2)$, and $I(\lambda_3)$. More generally, the illumination source **110** emits incident light **130** with a combination of m spectral bands characterized by $\lambda_{j=1, 2, \ldots, m}$, each having a corresponding intensity of $I(\lambda_1)$, $I(\lambda_2)$, . . . , $I(\lambda_m)$.

The imaging device **190** is any device or structure that detects reflected light **134** from article **150** and generates an image **126** of the article **150**. In one embodiment, the imaging device **190** may refer to a camera **114** that detects reflected light **134** and generates an image **126** of the article **150** including an array of pixels **118**, in which each pixel **118** has a corresponding scale or intensity I_{pixel}. In one particular embodiment referred to throughout the remainder of the specification, the image **126** is a grayscale image, in which the intensity I_{pixel} of a pixel **118** corresponds to a level on a quantified grayscale. For example, the intensity I_{pixel} of pixel **118** may correspond to a level on the 8-bit grayscale that quantifies the intensity of light from a scale of 0 to 255. As shown in FIG. **1**, grayscale image **126** has several black pixels **118** with the lowest intensity, several white pixels **118** with the highest intensity, and several gray pixels **118** with intensities in between the white and black pixels **118**. It is appreciated, however, that in other embodiments the image **126** is a color image, in which the color of a pixel **118** is a combination of quantified intensities on the RGB-scale.

The camera **114** maps a surface area element **154** of the article **150** to a corresponding pixel **118** intensity I_{pixel} by detecting the intensities of reflected light **134** from the surface area element. As shown in the example of FIG. **1**, a surface area element **154** of the article **150** is a small portion of the article **150** that may translate to a pixel on the image **126**. The article **150** is composed of multiple surface area elements **154**. Upon receiving illumination **130** with a single spectral band λ_j, the intensity φ_j of reflected light **134** from a surface element detected by a sensor (not shown) in the camera **114** is given by:

$$\varphi_j = I(\lambda_j) \cdot R(\lambda_j),$$

where $R(\lambda_j)$ is the surface reflectance of the surface area element for spectral band λ_j. That is, the intensity φ_j of reflected light **134** is the proportion of remaining incident light **130** that is reflected off of the surface area element **154** of article **150**, determined by the value $R(\lambda_j)$.

Upon detecting the reflected intensities $\varphi_{j=1, 2 \ldots, m}$ for all spectral bands (or from some number of spectral bands) from the illumination source **110**, the camera **114** in the FIG. **1** example multiplies, wavelength-by-wavelength, the reflected intensities $\varphi_{j=1, 2, \ldots, m}$ with the spectral response $T(\lambda_1)$, $T(\lambda_2)$, . . . , $T(\lambda_m)$ of the camera **114** for each spectral band. The camera **114** generates the intensity I_{pixel} for the corresponding pixel **118** by summing up the results across the spectral bands $\lambda_{j=1, 2, \ldots, n}$. Specifically, the intensity I_{pixel} of the pixel **118** is proportional to the sum:

$$I_{pixel} \propto \sum_{j=1}^{m} I(\lambda_j) \cdot R(\lambda_j) \cdot T(\lambda_j).$$

The above equation may refer to the pixel intensity of a single grayscale channel, or to the pixel intensity of any one of the red, green, and blue (RGB) channels of the camera **114**.

In another embodiment, the imaging device **190** may refer to an eye. That is, the image **126** may refer to an image **126** of the article **150** generated in the brain by processing the reflected intensities through structures or cells in the eye. Since the functionality of a camera **114** and the eye are similar, the system **100** may also adjust the individual illumination intensities of each spectral band of light on the article **150**, such that one observing the article **150** sees an optimized contrast between illuminated objects A and B.

Similarly to the embodiment of a camera **114**, the intensity of reflected light $I_{surface}$ of a corresponding surface area element **154** may be given by:

$$I_{surface} \propto \sum_{j=1}^{m} I(\lambda_j) \cdot R(\lambda_j) \cdot T(\lambda_j)$$

where $T(\lambda_j)$ is now the spectral response of the human eye. For example, the equation above may indicate the intensity of light or the strength of electrical signal generated by one or more photoreceptors of the eye by absorbing photons of short (S), medium (M), and long (L) wavelengths.

If each element $I(\lambda_j) \cdot T(\lambda_j)$ for all spectral bands $\lambda_{j=1, 2, \ldots, m}$ is concatenated into a column vector V, and if each reflectance value $R(\lambda_j)$ for all spectral bands $\lambda_{j=1, 2, \ldots, m}$ is concatenated into a column vector R, the intensity of the pixel **118** (or a corresponding surface area element **154**) can be reformulated as:

$$I_{pixel} \propto V^T R.$$

That is, the intensity I_{pixel} of the pixel **118** is a dot product of vector V associated with the quantities $I(\lambda_1) \cdot T(\lambda_1)$, $I(\lambda_2) \cdot T(\lambda_2)$, . . . , $I(\lambda_m) \cdot T(\lambda_m)$, and vector R associated with the reflectance values $R(\lambda_1)$, $R(\lambda_2)$, . . . , $R(\lambda_m)$ of the corresponding surface area element.

The illumination controller **160** receives an object setting **164** indicating the two or more objects A and B to be distinguished, and tunes the illumination intensities $I(\lambda_1)$, $I(\lambda_2)$, . . . , $I(\lambda_m)$ of incident light **130** through optimal illumination setting **168** such that the system **100** illuminates the article **150** to have optimized contrast between object A and object B when seen through an imaging device **190** such as a camera **114** or the eye. Specifically, when a camera **114** is used as the imaging device **190**, the system **100** having an optimal illumination intensity setting **168** for the illumination source **110** may generate an image **126**B such that the pixel intensity difference between the image portion of object A and the image portion of object B is greater compared to that of a conventional or un-optimized illumination intensity setting.

The optimal illumination setting **168** is found by analyzing past or present reflectance data associated with other instances of objects A and B and extracting a classification vector having a direction that separates reflectance values between the objects. Thus, by tuning the illumination intensities in the imaging system **100**, the system can generate an image in which the two objects look different or have a greater contrast that they would in an image in which the illumination intensities have not been tuned in this way. Returning to the example in the medical setting, there will be a much greater contrast between the anatomical structures that otherwise appeared very similar, such that the structures are clearly discernible to the physician as different anatomical structures. A more detailed description of the illumination controller **160** is provided below in reference to FIG. **3**.

Illumination Controller

FIG. **3** is a block diagram illustrating the illumination controller **160**, according to one embodiment.

The illumination controller **160** includes a training module **350**, a controller module **354**, a data store for training images **310**, and a data store for classification vectors **314**. Some embodiments of the illumination controller **160** have different or additional modules than the ones described here. Similarly, the functions can be distributed among the modules in a different manner than is described here. Certain modules and functions can be incorporated into other modules of the illumination controller **160**.

Training Module

The training module **350** receives a set of training data **310** that contains reflectance values for multiple instances of two or more objects A and B (e.g., different instances of a human bladder versus a human kidney), identifies a classification vector V_C that points along a direction separating the reflectance values between the two or more objects, and stores the identified classification vector V_C in classification vectors **314**.

Training Data

FIG. **4** illustrates example training data **310** provided to the training module **350** for identifying a classification vector, according to one embodiment.

The training data **310** contains a series of reflectance values $R(\lambda_j)$ for surface area elements of an object instance, across multiple instances of the object. As shown in FIG. **4**, the training data **310** contains a pair of matrices (X_{train}, y_{train}), in which each row is an entry corresponding to a surface area element of either an instance of object A or object B. Each column in X_{train} is an independent feature that corresponds to the collected reflectance value $R(\lambda_j)$ for the surface area element when illuminated with light from spectral band λ_j. Thus, the matrix X_{train} in FIG. **4** contains m columns or features, corresponding to reflectance values for each spectral band $\lambda_{j=1, 2, \ldots, m}$. The vector y_{train} is a column vector of already known labels indicating the object category of a corresponding entry in X_{train}. That is, each entry in y_{train} indicates the object category of the set of reflectance values $R(\lambda_j)$ in the corresponding entry. For example, the vector y_{train} in FIG. **4** contains labels indicating whether a corresponding entry in X_{train} belongs to either object A or object B.

Herein, a row of reflectance values $R(\lambda_1)$, $R(\lambda_2)$, . . . , $R(\lambda_m)$ for entry i in X_{train} is denoted as vector R_i, and the corresponding object label for the entry in y_{train} is denoted as y_i.

In one embodiment, the training data **310** is collected by sequentially illuminating an instance of an object (e.g., an instance of object A or B) with light from spectral bands λ_1, λ_2, . . . , λ_m, generating m images corresponding to each spectral band λ_j for that object, and extracting the reflectance values $R(\lambda_1)$, $R(\lambda_2)$, . . . , $R(\lambda_m)$ for the surface area elements composing the object. This process is repeated for multiple instances of the object. Thus, the reflectance values for an object are collected not only across multiple surface area elements composing the object, but also across multiple instances of the object. The reflectance values for an object may be collected by any one or a combination of integrating sphere measurements, Fourier transform infrared spectroscopy (FT-IR), or hyperspectral imaging, but is not limited thereto.

Identification of Classification Vector

FIG. **5** illustrates a classification vector V_C for two objects A and B, according to one embodiment.

The training module **350** identifies a classification vector V_C that points along a direction separating reflectance values between the two or more objects A and B. That is, the direction of the classification vector V_C travels from one set of reflectance values predominantly associated with one object category, to another set of reflectance values predominantly associated with a different object category. Since the classification vector V_C spans across reflectance values for m spectral bands $\lambda_{j=1, 2, \ldots, m}$, the classification vector is an m-dimensional vector in the spectral band space.

FIG. **5** shows a series of reflectance values $R(\lambda_1)$, $R(\lambda_2)$ for training data **310** entries belonging to object A (plotted with the symbol "X"), and reflectance values for training data **310** entries belonging to object B (plotted with the symbol "O"). Point **510** may correspond to the reflectance values in the first row of the training data **310**, given by vector R_1. Point **518** may correspond to the reflectance values in the second row of the training data **310**, given by vector R_2.

The training module **350** identifies a set of reflectance values containing points associated with one object category, and another set of reflectance values containing points associated with a different object category. For example, the set **526** identified by the training module **350** contains points mostly associated with object B, and the set **530** contains points mostly associated with object A. The training module **350** further identifies a classification vector V_C having a direction separating the two sets of reflectance values. As shown in FIG. **5**, the classification vector V_C points along a direction separating the reflectance values of objects A and B. In other words, the direction of the classification vector V_C travels from the set **526** of reflectance values associated with object A, to another set **530** of reflectance values associated with object B.

In one embodiment, the training module **350** identifies the classification vector V_C by training one or more classifiers that separate the reflectance values between two or more objects A and B. In one particular embodiment referred throughout the remainder of the specification, the classifier is a linear support vector machine classifier (SVM). It is appreciated, however, that in other embodiments the classifier can be any classifier that can classify a data point into one among multiple categories. For example, the classifier can be any classifier in which the classification is done by an inner product or a series of inner products, similarly to the linear SVM classifier.

FIG. **6** is an example classifier **610** trained by the training module **350**, according to one embodiment.

The training module **350** constructs a trained classifier **610** by extracting a weight vector w and a threshold parameter b from the training data **310**. The resulting classifier is a boundary in the form of a line or hyperplane that separates the feature space of the training data **310** into two or more disjoint regions, in which a set of reflectance values in one region is associated with a corresponding object category. In the example shown in FIG. **6**, the classifier **610** is a line dividing the two-dimensional feature space into one region **620** mostly containing reflectance values for object A, and another region **624** mostly containing reflectance values for object B.

The boundary constructed by the classifier **610** is a collection of points that satisfy a condition specified by a function of the weight vector w and the threshold parameter b. Specifically, the classifier **610** in FIG. **6** satisfies:

$$w^T R = b,$$

where w is the weight vector, b is the threshold parameter, R is a vector variable indicating any point in the feature space, and $w^T R$ is an affine classifying function. The numerical values of the weight vector w and the threshold parameter b are extracted from the training data **310** by the training module **350**.

In one embodiment, the training module **350** may identify the weight vector w perpendicular to the classifier **610** as the classification vector V_C. Since the classification vector V_C is perpendicular to the classifier **610**, and the classifier **610** is constructed as the boundary between reflectance values of different objects, the direction of the classification vector V_C naturally points along a direction that separates the different groups of reflectance values.

Alternatively, the training module **350** may identify classification vector V_C through other means than a classifier. For example, the training module **350** may train a cluster of reflectance values associated with object A, and another cluster associated with object B using any clustering algorithm. In such a case, the training module **350** may identify classification vector V_C to be the vector from a point within one cluster to another. As another example, the training module **350** may identify the classification vector V_C through various distance metrics between the reflectance values of the training data **310**, instead of extracting the classification vector V_C through an analytical model.

Returning to FIG. **5**, with regard to the projection $V_C^T R$ on the classification vector V_C, due to the separating direction of the classification vector V_C, the projection $V_C^T R$ for a set **526** of reflectance values associated with one object are grouped towards one end of the classification vector V_C including mostly low values, while the projection $V_C^T R$ for a set **530** of reflectance values associated with a different object are grouped towards the opposite end of the classification vector V_C including mostly higher values. For example, the projection **514** of point **510** associated with object B is of a lower value than the projection **522** of point **518** associated with object A.

Moreover, when the classification vector V_C is the weight vector w of the classifier **610**, the projection $V_C^T R$ is related to the perpendicular distance from the classifier **610**. Specifically, the projection $V_C^T R$ for reflectance values in region **620** increases as the distance is farther away from the classifier **610**, while the projection $V_C^T R$ for reflectance values in region **624** decreases as the distance is farther away from the classifier **610**. The relationship between the projection $V_C^T R$ and the imaging system **100** will be described in further detail in reference to the controller module **354** below.

In one embodiment, the training module **350** may identify a range of classification vectors instead of one classification vector V_C. For example, a range of classification vectors may be given by an interval centered around V_C:

$$V_C + \Delta(V_C),$$

where $\Delta(V_C)$ is a vector containing negative or positive elements within a predetermined range. After identifying the classification vector V_C or a range of classification vectors for two or more objects A and B, the training module **350** stores the identified classification vector or range in classification vectors **314**.

Controller Module

Returning to FIG. **3**, the controller module **354** receives an object setting **164** indicating two or more objects A and B to be distinguished, retrieves the corresponding classification vector for the objects A and B in classification vectors **314**, and outputs an optimal illumination setting **168** indicating the optimal intensities of the illumination source **110** that will generate an image **126**B of an article **150** with optimized contrast between the image portion of A and the image portion of B. The optimized illumination setting **168** mimics the values of the retrieved classification vector V_C. Article **150** may include a new instance of objects A and B that were not included in the training data **310**, but are of similar nature to those instances used in the training data **310**. Alternatively, article **150** may include instances of objects A and B that were included in the training data **310**.

Identification of Optimal Illumination Setting

After retrieving the corresponding classification vector V_C, the controller module **354** identifies the optimal illumination setting **168** by finding illumination intensities $I_{opt}(\lambda_1)$, $I_{opt}(\lambda_2)$, . . . , $I_{opt}(\lambda_m)$ that result in the quantity $T(\lambda_j)\cdot I(\lambda_j)$ being equal to or proportionate to the j-th element of the classification vector V_C for each spectral band $\lambda_{j=1, 2, \ldots, m}$. This condition is given by:

$$T(\lambda_j)\cdot I_{opt}(\lambda_j)\propto[V_C]_j, \forall j=1,2,\ldots,m,$$

where $[V_C]_j$ denotes the j-th element of V_C. Since the spectral response $T(\lambda_j)$ may be different for each type of imaging device **190**, the optimal illumination setting **168** may differ depending on the type of imaging device **190** used in the system **100**. For example, the spectral response of a camera **114** may significantly differ from the eye, leading to different optimal illumination settings **168** depending on the type of imaging device **190**.

In one embodiment, the optimal illumination intensities $I_{opt}(\lambda_1)$, $I_{opt}(\lambda_2)$, . . . , $I_{opt}(\lambda_m)$ may be a scalar multiple of the elements of classification vector V_C. In another embodiment, the illumination intensities $I_{opt}(\lambda_1)$, $I_{opt}(\lambda_2)$, . . . , $I_{opt}(\lambda_m)$ may be a translation of the elements of classification vector V_C. That is, the optimal illumination intensity $I_{opt}(\lambda_j)$ may be given by:

$$I_{opt}(\lambda_j)=c_{0j}\cdot[V_C]_j+c_{1j}, \forall j=1,2,\ldots,m,$$

where c_{0j}, c_{1j} are constants. For example, the controller module **354** may offset the values of the classification vector V_C, if the classification vector V_C contains negative elements. Specifically, the controller module **354** may offset the elements of the classification vector by the negative most element in V_C, such that the translated elements are all positive. As another example, the controller module **354** may take the absolute values of the classification vector V_C in determining the optimal illumination intensities.

The controller module **354** may also identify an optimal illumination setting **168** containing a range of optimal illumination intensities. For example, the range of optimal illumination intensities for spectral band λ_j may be given by an interval centered around $I_{opt}(\lambda_j)$:

$$I_{opt}(\lambda_j)+\Delta_{opt}(\lambda_j),$$

where **66** $_{opt}(\lambda_j)$ is a negative or positive value within a predetermined range. As another example, the controller module **354** may identify a range of optimal illumination intensities as the optimal illumination setting **168** by translating or scaling a range of classification vectors received from the training module **350**.

Relationship Between Pixel Intensity and Projection

In the embodiment of a camera **114** as the imaging device **190**, the resulting intensity of a pixel I_{pixel} in the image **126**B generated using the optimal illumination setting **168** is proportional to the projection $V_C{}^T R$ of its corresponding surface area element reflectance onto the classification vector V_C. As described in further detail in reference to FIG. **7**, the corresponding image **126**B generated using the optimal illumination setting **168** for two or more objects A and B retains a high contrast between the pixel intensities for object A and object B.

As discussed in reference to FIG. **1**, the imaging process itself resulted in the pixel intensity I_{pixel} to be determined by the relationship:

$$I_{pixel}\propto V^T R,$$

where each element in V contains the quantity $I(\lambda_j)\cdot T(\lambda_j)$ of each spectral band λ_j, and each element in R contains the reflectance value $R(\lambda_j)$ of each spectral band λ_j for a corresponding surface area element.

Consequently, if the illumination intensities $I(\lambda_1)$, $I(\lambda_2)$, . . . , $I(\lambda_m)$ are set within a range specified by the optimal illumination setting **168**, the intensity of a pixel I_{pixel} in image **126** will be proportional to the projection $V_C{}^T R$ of its surface area element reflectance vector onto the classification vector V_C. This relationship is given by:

$$I_{pixel}\propto V^T R\propto V_C{}^T R.$$

Similar relationships between light intensity and the classification vector can be deduced for other type of imaging devices **190**, such as the eye.

FIG. **7** illustrates the relationship between pixel intensity I_{pixel} in image **126**, and the projection of the corresponding surface area element reflectance onto the classification vector V_C retrieved from the classifier **610** in FIG. **6**, according to one embodiment.

As shown in FIG. **7**, point **708** represents reflectance values $R(\lambda_1)$, $R(\lambda_2)$ for a surface area element associated with object A illuminated under the optimal illumination setting **168**. Similarly, point **712** represents reflectance values for an element associated with object B. As discussed above, points **708** and **712** may indicate reflectance values from new instances of objects A and B that were not available in the training data **310**, or indicate reflectance values from instances of objects A and B that were available in the training data **310**.

In the case of a new instance of objects A and B, the projection of the reflectance values onto the identified classification vector $V_C{}^T R$ have similar distributions to that identified for the training data **310**, since the article **150** illuminated by the optimal illumination setting **168** contains an instance of objects A and B with similar nature to those instances used in the training data **310**.

That is, for both reflectance values available and unavailable in the training data **310**, the projections $V_C{}^T R$ associated with one object are mapped to low values, while the projections associated with a different object are mapped to higher values. Moreover, the pixel intensity I_{pixel} that results from the optimal illumination setting **168** is proportional to the projection $V_C{}^T R$. Thus, in the process of imaging, the pixel intensities I_{pixel} for surface area elements associated with one object category are mapped to low values, while the intensities for a different object category are mapped to higher values, resulting in a high-contrast image **126** of the objects.

For example, as shown in FIG. **7**, the projection of a new point **708** associated with object A is mapped to a high value z_1 because the reflectance of the corresponding surface area element is distributed within the region **620**. As a result, the intensity of the corresponding pixel is a light-gray color indicated by **730**. As another example, the projection of point **712** associated with object B is mapped to a lower value z_3 because the reflectance of the corresponding surface area element is distributed within the region **624**. As a result, the corresponding pixel results in a dark-gray color indicated by **738**.

In one embodiment, the intensities of the pixels I_{pixel} can be mapped to color scales other than the grayscale. For example, the camera **114** may map pixel intensities I_{pixel} to intensities of a single color (e.g., red) instead of the grayscale. As another example, the pixel intensities I_{pixel} may be mapped to a red-green color scale, in which low intensities are mapped towards the red color and high intensities are mapped towards the green color, or vice versa. As another

example, the pixel intensities may be mapped along any dimension of a color space (e.g., Lab color space, XYZ color space, etc.).

As a result of the separation of reflectance values, the contrast between the image portions of different objects in the optimized image generated by the optimal illumination setting **168** may be higher than that in an image generated by a conventional illumination intensity setting outside the range of the optimal illumination setting **168**. Specifically, the difference between pixel intensities of the different image portions in an optimized image generated by the optimal illumination setting **168** may be larger than that in an image generated by a conventional illumination intensity setting outside the range of the optimal illumination setting **168**. As another example, the difference between electrical signals generated by one or more photoreceptors of the eye for the different portions under an optimal illumination setting **168** may be larger than that of a conventional illumination setting outside the range of the optimal illumination setting **168**.

FIG. **8** shows an un-optimized image **810** of turkey meat and chicken meat under conventional illumination, and an optimized image **820** of the same under optimal illumination.

As shown in FIG. **8**, the system **100** generates a low-contrast image **810** of chicken meat **850** and turkey meat **854** under conventional illumination. In contrast, the system **100** generates a high-contrast image **820** of chicken meat **858** and turkey meat **862** under optimal illumination using a classification vector extracted through the training module **350**. Pixels corresponding to chicken meat **858** are mapped to low intensities, while pixels corresponding to turkey meat **862** are mapped to higher intensities. Similarly, in a medical setting, different anatomical structures, organs, tissues, tissue states or properties, etc. that might appear similar in the low-contrast image under conventional illumination will appear distinct under the illumination settings using the classification vector extracted through the training module **350**. Thus, the physician can immediately distinguish between two organs that might outside of these settings appear nearly the same, thereby avoiding mistakes and improving patient outcomes, and also saving time associated with a medical procedure or diagnosis.

In one embodiment, the illumination controller **160** may determine to use only select spectral illumination sources based on the magnitude of the classification vector elements. For example, the illumination controller **160** may illuminate the article **150** with spectral illumination sources corresponding to elements of the classification vector that have a magnitude above a predetermined threshold. A classification vector element $[V_C]_j$ having a high weight indicates that the reflectance values between the different object categories are highly separated along the spectral band λ_j, and thus, indicates that the spectral illumination source for the spectral band should be used for enhancing the contrast between the different objects.

FIG. **9** is a flowchart illustrating the process of generating an image with optimized contrast between two or more objects A and B using an imaging system, such as the imaging system of FIG. **1** or one or more components thereof, according to one embodiment.

The imaging system **100** or a component thereof receives **910** an indication to compare a first object and a second object. For example, this may be an instruction by a user, such as a physician, to compare two structures (e.g., two human or animal organs) or an instruction to generate images of two structures. The imaging system **100** accesses **912** the corresponding classification vector for the first object and the second object. The classification vector is extracted by separating reflectance values for the first object from the reflectance values for the second object. The optimized illumination intensities for the spectral illumination sources are determined **914** based on the retrieved classification vector. The first object and the second object are illuminated **916** with spectral bands of light having the determined illumination intensities. An image of the first object and the second object is generated **918** based on the reflected intensities of the spectral bands of light reflected off of the first object and the second object. An optimized contrast image(s) of the first object and the second object are provided **920** for display.

In another embodiment, the method includes a component of an imaging system or a module associated with an imaging system that interacts with the imaging system. For example, the controller module **354** might operate separate from the imaging system. In this case, the controller module receives **910** from the imaging system and indication to compare two objects or receives an object setting, accesses **912** the corresponding classification vector for the objects, and determines **914** the optimized illumination intensities for the spectral illumination sources based on the classification vector, and the spectral response of the imaging device **190**. The module then sends to the imaging system the appropriate illumination settings that can then be used as settings for the illumination sources of the imaging system in illuminating the objects to ultimately generate the image of the objects. Thus, the steps **916** and **918** are performed by the imaging system, and the separate controller module simply sends to the imaging system the illumination intensities to use in generating a high-contrast image.

FIG. **10** is a block diagram of a computer **1000** for implementing the illumination controller **160**, according to one embodiment.

The computer **1000** includes at least one processor **1002** coupled to a chipset **1004**. The chipset **1004** includes a memory controller hub **1020** and an input/output (I/O) controller hub **1022**. A memory **1006** and a graphics adapter **1012** are coupled to the memory controller hub **1020**, and a display **1018** is coupled to the graphics adapter **1012**. A storage device **1008**, an input device **1014**, and network adapter **1016** are coupled to the I/O controller hub **1022**. Other embodiments of the computer **1000** have different architectures.

The storage device **1008** is a non-transitory computer-readable storage medium such as a hard drive, compact disk read-only memory (CD-ROM), DVD, or a solid-state memory device. The memory **1006** holds instructions and data used by the processor **1002**. The input interface **1014** is a touch-screen interface, a mouse, track ball, or other type of pointing device, a keyboard, or some combination thereof, and is used to input data into the computer **1000**. In some embodiments, the computer **1000** may be configured to receive input (e.g., commands) from the input interface **1014** via gestures from the user. The graphics adapter **1012** displays images and other information on the display **1018**. The network adapter **1016** couples the computer **1000** to one or more computer networks.

The types of computers **1000** can vary depending upon the embodiment and the processing power required by the entity. The computers **1000** can lack some of the components described above, such as graphics adapters **1012**, and displays **1018**.

Other Considerations

Some portions of the above description describe the embodiments in terms of algorithmic processes or operations. These algorithmic descriptions and representations are commonly used by those skilled in the data processing arts to convey the substance of their work effectively to others skilled in the art. These operations, while described functionally, computationally, or logically, are understood to be implemented by computer programs comprising instructions for execution by a processor or equivalent electrical circuits, microcode, or the like. Furthermore, it has also proven convenient at times, to refer to these arrangements of functional operations as modules, without loss of generality. The described operations and their associated modules may be embodied in software, firmware, hardware, or any combinations thereof.

As used herein any reference to "one embodiment" or "an embodiment" means that a particular element, feature, structure, or characteristic described in connection with the embodiment is included in at least one embodiment. The appearances of the phrase "in one embodiment" in various places in the specification are not necessarily all referring to the same embodiment.

Some embodiments may be described using the expression "coupled" and "connected" along with their derivatives. It should be understood that these terms are not intended as synonyms for each other. For example, some embodiments may be described using the term "connected" to indicate that two or more elements are in direct physical or electrical contact with each other. In another example, some embodiments may be described using the term "coupled" to indicate that two or more elements are in direct physical or electrical contact. The term "coupled," however, may also mean that two or more elements are not in direct contact with each other, but yet still co-operate or interact with each other. The embodiments are not limited in this context.

As used herein, the terms "comprises," "comprising," "includes," "including," "has," "having" or any other variation thereof, are intended to cover a non-exclusive inclusion. For example, a process, method, article, or apparatus that comprises a list of elements is not necessarily limited to only those elements but may include other elements not expressly listed or inherent to such process, method, article, or apparatus. Further, unless expressly stated to the contrary, "or" refers to an inclusive or and not to an exclusive or. For example, a condition A or B is satisfied by any one of the following: A is true (or present) and B is false (or not present), A is false (or not present) and B is true (or present), and both A and B are true (or present).

In addition, use of the "a" or "an" are employed to describe elements and components of the embodiments herein. This is done merely for convenience and to give a general sense of the disclosure. This description should be read to include one or at least one and the singular also includes the plural unless it is obvious that it is meant otherwise.

Upon reading this disclosure, those of skill in the art will appreciate still additional alternative structural and functional designs for generating an image with optimized contrast using an imaging system. Thus, while particular embodiments and applications have been illustrated and described, it is to be understood that the described subject matter is not limited to the precise construction and components disclosed herein and that various modifications, changes and variations which will be apparent to those skilled in the art may be made in the arrangement, operation and details of the method and apparatus disclosed herein.

What is claimed is:

1. An imaging system comprising:

one or more spectral illumination sources; and

a controller comprising a computer configured to:

receive an indication to compare a first object and a second object;

access a classification vector for the first object and the second object, the classification vector having been extracted by separating a plurality of collected reflectance values for the first object from a plurality of collected reflectance values for the second object;

determine, from the extracted classification vector, an optimized set of illumination intensities; and

operate the one or more spectral illumination sources to simultaneously provide illumination to the first object and the second object with one or more spectral bands of light having the optimized set of illumination intensities.

2. The system of claim **1**, wherein determining the optimized set of illumination intensities comprises determining a set of illumination intensities optimized to increase contrast between the first object and the second object when imaged using a particular camera.

3. The system of claim **1**, wherein determining the optimized set of illumination intensities comprises determining a set of illumination intensities optimized to increase perceived contrast between the first object and the second object when observed by a human eye.

4. The system of claim **1**, wherein the plurality of collected reflectance values for the first object and the second object are separated by a support vector machine (SVM) classifier.

5. The system of claim **4**, wherein the classification vector is extracted as a weight vector of the SVM classifier.

6. The system of claim **1**, wherein the plurality of collected reflectance values for the first object and the second object are separated by a clustering algorithm to generate a cluster of reflectance values associated with the first object and a cluster of reflectance values associated with the second object.

7. The system of claim **6**, wherein a vector pointing from the cluster associated with the first object to the cluster associated with the second object is extracted as the classification vector.

8. The system of claim **1**, wherein each of the illumination intensities for the one or more spectral illumination sources have a one-to-one correspondence with each of the elements of the classification vector.

9. The system of claim **1**, wherein the computer is further configured to determine the illumination intensities by scaling elements of the classification vector by a first constant, and/or by translating the elements of the classification vector by a second constant.

10. A non-transitory computer readable medium configured to store at least executable instructions, wherein the executable instructions, when executed by a processor of a computing device, cause the computing device to perform functions comprising:

receiving an indication to compare a first object and a second object with an imaging system;

accessing a classification vector for the first object and the second object, the classification vector having been extracted by separating a plurality of collected reflectance values for the first object from a plurality of collected reflectance values for the second object;

determining, from the extracted classification vector, an optimized set of illumination intensities to apply to one

or more spectral illumination sources of the imaging system based on a spectral response of an imaging device of the imaging system, each of the one or more spectral illumination sources configured to provide illumination to the first object and the second object with one or more spectral bands of light having the optimized set of illumination intensities; and

providing to the imaging system the optimized set of illumination intensities for simultaneously illuminating the first object and the second object with the one or more spectral bands of light having the optimized set of illumination intensities.

11. The non-transitory computer readable medium of claim **10**, wherein determining the optimized set of illumination intensities comprises determining a set of illumination intensities optimized to increase contrast between the first object and the second object when imaged using a particular camera.

12. The non-transitory computer readable medium of claim **10**, wherein determining the optimized set of illumination intensities comprises determining a set of illumination intensities optimized to increase perceived contrast between the first object and the second object when observed by a human eye.

13. The non-transitory computer readable medium of claim **10**, wherein determining the optimized set of illumination intensities further comprises:

identifying a range of optimized illumination intensities from the classification vector; and

determining the optimized set of illumination intensities from within the range of optimized illumination intensities.

14. The non-transitory computer readable medium of claim **10**, wherein the plurality of collected reflectance values for the first object and the second object are separated by a support vector machine (SVM) classifier.

15. The non-transitory computer readable medium of claim **14**, wherein a weight vector of the SVM classifier is extracted as the classification vector.

16. The non-transitory computer readable medium of claim **10**, wherein the plurality of collected reflectance values for the first object and the second object are separated by a clustering algorithm to generate a cluster of reflectance values associated with the first object and a cluster reflectance values associated with the second obj ect.

17. The non-transitory computer readable medium of claim **16**, wherein a vector pointing from the cluster associated with the first object to the cluster associated with the second object is extracted as the classification vector.

18. The non-transitory computer readable medium of claim **10**, wherein the illumination intensities are determined by scaling elements of the classification vector by a first constant, or by translating the elements of the classification vector by a second constant.

19. The non-transitory computer readable medium of claim **10**, wherein the classification vector is extracted by:

collecting one or more instances of the first object and one or more instances of the second object;

illuminating the instances of the first object and the instances of the second object with each individual spectral band of light from the one or more spectral bands of light;

generating one or more maps corresponding to the one or more spectral bands of light for each instance of the first object and each instance of the second object, each map comprising an array of pixels based on reflected intensities of the corresponding spectral band of light;

identifying a subset of pixels corresponding to an instance of the first object or an instance of the second object in each map; and

extracting the plurality of reflectance values for the first object and the plurality of reflectance values for the second object from the subset of pixels identified in each map.

20. The non-transitory computer readable medium of claim **19**, wherein generating the one or more maps further comprises:

for each pixel, detecting the reflected intensity of the corresponding spectral band of light reflected off of a surface area of an instance of the first object or an instance of the second object; and

generating the intensity of the pixel in the map proportionate to the detected reflected intensity.

* * * * *