(12) INTERNATIONAL APPLICATION PUBLISHED UNDER THE PATENT COOPERATION TREATY (PCT)

(19) World Intellectual Property Organization
International Bureau

(43) International Publication Date
04 January 2024 (04.01.2024)

WIPO | PCT

(10) International Publication Number
WO 2024/006586 A2

(51) International Patent Classification:
A61B 8/00 (2006.01) *G16H 30/00* (2018.01)

(21) International Application Number:
PCT/US2023/031824

(22) International Filing Date:
01 September 2023 (01.09.2023)

(25) Filing Language: English

(26) Publication Language: English

(30) Priority Data:
63/367,529 01 July 2022 (01.07.2022) US

(71) Applicant: **HNU PHOTONICS LLC** [US/US]; 350 Hoohana Street, Kahului, HI 96732 (US).

(72) Inventor: **O'CONNELL, Daniel, G.**; 779 Kumulani Drive, Kihei, HI 96753 (US).

(74) Agent: **MCGOWAN, Malcolm, K.** et al.; Cermak Nakajima & McGowan LLP, 2000 Duke Street, Suite 300, Alexandria, VA 22314 (US).

(81) Designated States *(unless otherwise indicated, for every kind of national protection available)*: AE, AG, AL, AM, AO, AT, AU, AZ, BA, BB, BG, BH, BN, BR, BW, BY, BZ, CA, CH, CL, CN, CO, CR, CU, CV, CZ, DE, DJ, DK, DM, DO, DZ, EC, EE, EG, ES, FI, GB, GD, GE, GH, GM, GT, HN, HR, HU, ID, IL, IN, IQ, IR, IS, IT, JM, JO, JP, KE, KG, KH, KN, KP, KR, KW, KZ, LA, LC, LK, LR, LS, LU, LY, MA, MD, MG, MK, MN, MU, MW, MX, MY, MZ, NA, NG, NI, NO, NZ, OM, PA, PE, PG, PH, PL, PT, QA, RO, RS, RU, RW, SA, SC, SD, SE, SG, SK, SL, ST, SV, SY, TH, TJ, TM, TN, TR, TT, TZ, UA, UG, US, UZ, VC, VN, WS, ZA, ZM, ZW.

(84) Designated States *(unless otherwise indicated, for every kind of regional protection available)*: ARIPO (BW, CV, GH, GM, KE, LR, LS, MW, MZ, NA, RW, SC, SD, SL, ST, SZ, TZ, UG, ZM, ZW), Eurasian (AM, AZ, BY, KG, KZ, RU, TJ, TM), European (AL, AT, BE, BG, CH, CY, CZ, DE, DK, EE, ES, FI, FR, GB, GR, HR, HU, IE, IS, IT, LT, LU, LV, MC, ME, MK, MT, NL, NO, PL, PT, RO, RS, SE, SI, SK, SM, TR), OAPI (BF, BJ, CF, CG, CI, CM, GA, GN, GQ, GW, KM, ML, MR, NE, SN, TD, TG).

Published:
— *without international search report and to be republished upon receipt of that report (Rule 48.2(g))*
— *with information concerning request for restoration of the right of priority in respect of one or more priority claims (Rules 26bis.3 and 48.2(b)(vii))*

WO 2024/006586 A2

(54) Title: NON-CONTACT DIAGNOSTIC SYSTEM

(57) **Abstract:** A non-contact system to rapidly diagnose specific diseases as well as measuring vitals without collection and handling of biohazardous materials. System fuses information from multiple independent and dissimilar sensors to maximize disease diagnostic accuracy as well as vital signs. System can be used to screen subjects entering venues avoiding communicable diseases or for regular clinical visits. Applies machine learning approaches that are transparent enough for human evaluation and require minimal training samples.

NON-CONTACT DIAGNOSTIC SYSTEM

CROSS-REFERENCE TO RELATED APPLICATIONS

[001] This application claims priority from US Provisional Application 63/367,529, filed 1 July 2022, the contents of which are incorporated herein in their entirety.

SUMMARY

[002] The system is used to make health assessments of human subjects and is comprised of a sensor head unit **10**, a positioning system **20** and a connected computer **30** (Figure 1) that may include an internet connection for remote analysis. The positioning system **20** is used to adjust the sensor head unit to the height of the subject, for example using a mechanized elevator **23**. The positioning system is utilized to view the subject in the desired direction and orientation to collect data of interest pertaining to a particular health condition. For example, a gimbal **22** can provide the head unit **10** pan **24** and tilt **25**control to orient the sensors correctly. The positioning system is controlled by a computer **30** using feature detection algorithms. For example an artificial intelligence face, mouth, or eye detector can be used to align the sensor head unit based on the location of the region of interest such as face, mouth, or eyes within the field of view (FOV) of the desired sensor.

[003] The sensor head unit **10** incorporates a thermal imaging sensor **11**, at least one visible or infrared imaging sensor **12** capable of narrow FOV, at least one visible or infrared imaging sensor capable of wide FOV **13** or an imaging sensor capable of both wide and narrow FOV using a mechanized zoom lens, and at least one hyperspectral imaging sensor **14** shown in **Error! Reference source not found.**.

[004] The sensor head unit **10** may also include at least one light source **15** attached internal or external to the sensor head for controlled illumination, a LIDAR ("**Li**ght **D**etection **a**nd **R**anging") sensor **16** or multiple LIDAR sensors **17** , and at least one control circuit board. The LIDAR unit **16** or multiple units **17** may also be used to measure distance or depth information and generate a 3D model of a scene. The LIDAR may be used to ensure the subject is located at a predetermined distance from the head unit as shown in **Error! Reference source not found.**.

Brief Description of the Drawings

[005] Figure 1: schematic diagram of a system described herein.

[006] Figure 2: schematic diagram of the sensor head unit.

[007] Figure 3: diagram showing human subject positioned for multi-sensor disease detection.

[008] Figure 4: representations of recorded image data.

[009] Figure 5: flowchart showing the process for generating a health assessment score.

[010] Figure 6: narrow FOV image of an eye (top) and the same image with an iris mask and sclera mask (bottom).

[011] Figure 7: flowchart showing steps in processing of eye images.

[012] Figure 8: flowchart showing steps in feature extraction from processed eye images.

[013] Figure 9: example of high density histogram (HDH) showing one-dimensional (left) and three-dimensional (right) representations.

[014] Figure 10: schematic representation of separation metric is used to identify the evaluation criteria conditions where positive subjects and negative subjects are most distinctive.

[015] Figure 11: A recorded picture of a scene consisting of an open mouth (left) and a representation of the collected spectral data (right).

[016] Figure 12: A diagram illustrating back projection techniques used to isolate the specific portions of the recorded spectral information that relate to the spectral composition of the target region of interest and produce spectral intensity vs wavelength profiles as an output.

[017] **Error! Reference source not found.** shows a face automatically segmented for the forehead, eyes, nose, cheeks, and mouth.

[018] Figure 14: Flowchart showing process for extraction of multiple features from spectral, thermal, and imaging sensors.

[019] Figure 15: Flowchart showing preprocessing of raw features

[020] Figure 16: schematic of pre-processing system.

[021] Figure 17: schematic of inference process.

Disease Detection Process Fusing Data From Multiple Sensors

[022] The system performs disease detection by fusing information from multiple sensors: thermal imaging sensor **11**, one or more visible or infrared imaging sensors (**12, 13**), and one or more hyperspectral sensor. Each sensor produces one or more images or data sets per subject (a person undergoing a test). **Error! Reference source not found.** shows how information is fused to develop a health assessment score for a particular vital, health feature or disease that the system had been trained on. In training the algorithms for disease detection, a set of mouth, face, and eye images are collected for disease positive subjects and a set for disease negative subjects. The system can be trained for a variety of diseases using the same image data set.

Narrow FOV Eye Sensor

[023] One sensor **12** of the system utilizes narrow FOV images of the eyes (top of Figure 6) to detect specific diseases through a machine learning training process using the blood vessels and other regions of interest within the eyes. The process was designed so that a minimal number of training subjects would be necessary as it can be time-consuming and expensive to collect the hundreds or thousands of subjects required by currently available artificial intelligence neural network frameworks. The process was further designed for transparency so that decisions made could be interpreted by humans that could then impose knowledge-based algorithm adjustments based on measured pathology features to improve accuracy. In contrast, artificial neural networks are more like black boxes because the trained "weights" are not humanly interpretable.

Feature Extraction and High Dimensional Histograms

[024] The following steps are performed to extract relevant anatomically rooted features from images of the eyes that pertain to pathological conditions. (1) Detect and segment the eye into the iris mask and sclera mask (bottom of **Error! Reference source not found.**). Masks are binary images indicating Regions of Interest (ROI). In the figure, the iris mask is denoted in the region with horizontal lines and the sclera mask is denoted with a checkerboard pattern. The segmentation step is performed by a trained artificial intelligence framework which is not part of the claims in this application. (2) Image arrays are converted to floating point to increase

dynamic range and avoid saturation. This step is shown in Block 2 in **Error! Reference source not found.**. (3) Normalize and standardize the images to calibrate and account for variations in ambient lighting. This step is shown in Block 3. (4) Increase image contrast and remove low spatial frequency variations as shown in Block 4. (5) The blood vessels are detected by using an edge detection algorithm as shown in Block 5. (6) Edge detection and adaptive thresholding is used forming a binary mask representing location of blood vessels. This is shown in Block 6. This results in a preliminary blood vessel mask. (7) Using an edge thinning algorithm as shown in Block 7, the blood vessel masks are thinned representing the "inner core" of the blood vessels. (8) Binary dilation (Block 8) is performed to thicken the cores to encompass the whole blood vessels' thickness. This forms the blood vessel mask in Block 9. (9) A spatial segmentation algorithm shown in Block 10 is used to segment the blood vessel mask into individual blood vessels that are spatially isolated from others (*i.e.,* mask of each detected blood vessel is not in contact with others). Each blood vessel is a region of interest. (10) The regions surrounding the individual blood vessels are also of interest. To create these masks, each blood vessel binary mask is dilated. Then the blood vessel mask is subtracted forming a surrounding mask for each blood vessel. These steps are illustrated in **Error! Reference source not found.** in Blocks 11 and 12. The thickness of these surrounding regions is tunable. After the blood vessel detection and segmentation process, the individual blood vessels are sorted over a variety of criteria including but not limited to length, distance from iris, chromatic brightness, chromatic ratios, texture, and any mixture as shown in **Error! Reference source not found.**. Features are extracted from the sorted list. These could include, for example, the ratio of the mean color values inside of a blood vessel with the mean of the color values in the region surrounding the blood vessel. This ratio is compared with the N largest blood vessels. This analysis results in one of several features that will be used in the training process. The sorting and feature extraction are summarized in **Error! Reference source not found.**.

[025] In addition to the features discussed above, there are high dimensional histograms (HDH) that also contribute to the training process. An example of a HDH is shown in **Error! Reference source not found.**. Basic histograms are one dimensional and discretized into a number of bins that contain a count of occurrences of particular quantities within a

measurement (such as an image or other sensor output). Histograms are an implementation of Probability Distribution Functions (PDF). In the case of the current HDH, values of every pixel color values are transformed into an HDH. The axes of the HDH are defined by the anatomically rooted features from the images. A simple three-dimensional example: axis one is the ratio of the red color pixel value to the blue color pixel value, axis two is the standard deviation of the green color pixel value over all pixels adjacent to the center pixel, and axis three is the pixel distance from the iris (**Error! Reference source not found.**). In training, a set of HDH is created for disease negative subjects and a separate set is created for positive subjects. A separation metric is used to identify the evaluation criteria conditions where positive subjects and negative subjects are most distinctive which are denoted as "extremes" in **Error! Reference source not found.**. The separation metric measures the distance between the average values for the positives and the average values for the negatives, divided by the larger of the two standard deviations. The identified evaluation criteria are used in the training process and from this point forward, the values for these specific HDH axis locations will be treated as "features" as defined above.

Feature Extraction for Spectral Sensor

[026] In addition to the narrow FOV images of the eye, **Error! Reference source not found.** also refers to the use of spectral sensor image information to include in the health assessment process conducted by the system. These spectral sensor images of the subject can include but are not limited to spectral images of the mouth and eyes. An example of this process when collecting spectral image information from an open human mouth is shown in **Error! Reference source not found.**. A recorded picture of a scene consisting of an open mouth is shown on the left portion of the image and a representation of the collected spectral data is shown to the right.

[027] Back projection techniques are used to isolate the specific portions of the recorded spectral information that relate to the spectral composition of the target region of interest and produce spectral intensity vs wavelength profiles as an output. This output is used to contribute to the health assessment process conducted by the system.

[028] As an example in **Error! Reference source not found.**, the black region in the mouth indicates the location of the automatically segmented region of interest from the recorded image of the scene. Based on the specified region of interest, the associated portions of the spectral information that relate to the composition of wavelength spectral information for points within the scene ROI are isolated and are analyzed to produce spectral intensity profiles for the given region of interest. This output of the spectral sensor, the spectral intensity profiles from single or multiple regions of the scene, is interrogated for features. Some features will be more prominent in disease positive subjects, and others in disease negative subjects. Features can include wavelengths where peaks occur or linearity and slope within various spans of wavelength.

Feature Extraction for Thermal Imaging Sensor

[029] The final sensor input referred to in **Error! Reference source not found.** is the thermal imaging sensor, capable of recording images of the subject that includes but is not limited to thermal images of the face. **Error! Reference source not found.** shows a face automatically segmented for the forehead, eyes, nose, cheeks, and mouth. Features from these segmented regions are extracted. These features can be averages, variances, skewness, kurtosis, ratios, and other properties. Another source of features for the disease detection process are spatial gradient profiles. In each of the regions (forehead, eyes, nose, cheeks, and mouth), spatial gradients are observed. As an example, coefficients from polynomial regression algorithms fitted to the spatial gradient profiles are treated as features that will be used in the disease and health assessment process.

[030] The multiple sensor dataset using feature extraction used for disease detection as described in this embodiment can also be used to measure human vital signs.

Disease Detection: Training Process

[031] The disease detection process outlined in this section is one example of many (including artificial neural networks) that simultaneous uses the features extracted from multiple independent sensors in a training process to maximize disease detection capability. As with the

narrow FOV eye image, multiple features are extracted from each of the sensors. These features are organized as shown in **Error! Reference source not found.**. In the figure, features are extracted from the spectral sensor image for both disease negative and positive subjects. These features can be items such as the inflection wavelengths, peaks within the Fourier transform, local peaks at various wavelengths, or other features. In the case of thermal images, statistical and other features are extracted along with coefficients from fitting directional profiles within the regions of interest. For the eye image, features are extracted along with the HDH's for both disease negative and positive subjects. In the training process, the eye image HDH from the disease negative subjects are compared with those from the disease positive subjects. This comparison looks for HDH locations that maximally separate disease positives from negatives as previously shown in **Error! Reference source not found.**. The feature extraction step results in a large number of features for each disease positive and negative subject. These features individually might have limited accuracy in their ability to identify disease positive and negative subjects, but when multiple features are used jointly, the accuracy will be increased provided a good selection of highly separative independent features. This jointness is achieved by organizing the features into dimensions. This organization behaves like a classical Bayesian classifier, but for several simultaneous known features. In **Error! Reference source not found.**, the "High Sep. Bins" block identifies the extremes from **Error! Reference source not found.**. This provides the location within the HDH's where disease negative and positive subjects differ the most over a training set. The "High Dim. Classifier" or high dimensional classifier with D dimensions and produces a separation metric (as previously discussed) for a set of D training positive subject features and a set of the same D negative subject features. The classifier uses a limited number of dimensions, D, which is far less than the number of K total features extracted. For example, D may range from 3 to 9 dimensions or higher. In the training process, a series of features are selected for each dimension. The high dimensional classifier projects the D dimensions for each iteration (different combination of features for each dimension) onto 1 dimension. Then, a separation metric is noted for that iteration (and set of features). The high dimensional classifier selects the feature set that produced the highest separation metric. Along

with the feature set, the projection and other information is stored for future inference. This is the output shown in the right-most block of **Error! Reference source not found.**.

[032] **Error! Reference source not found.** further illustrates the high dimensional classifier referred to above. There are N negative subjects in the training set and P positive subjects. There are K features extracted and there are D dimensions and K is greater than D. For the negative set, a N by K matrix (N rows by K columns) of features is formed. For the positive set, a P by K matrix (P rows by K columns) of features is formed. The shaded columns in **Error! Reference source not found.** represent a set of D features selected for a particular iteration. These features are fed into a Principal Component Algorithm (PCA) unit which computes a D dimensional vector between the disease positives subjects and disease negatives subjects that maximizes variance along the vector. The vector is then projected onto a single dimension and a separation metric is noted for a given iteration.

[033] Prior to the application of the PCA, the raw features may be pre-processed as shown in **Error! Reference source not found.**. The pre-processing is described in **Error! Reference source not found.**. Each column is concatenated into a single array for the purpose of normalization and standardization. The average of each combined column is subtracted from the column. Next, each of the combined columns are divided by their greatest quantile (for example, the value of the column at its 90^{th} percentile point). These quantiles (for each combined column) are stored for later inference (the process where disease detection is performed on individuals). After the division, the averages of each of the combined columns are re-added to their respective original (non-combined) columns.

Disease Detection: Inference

[034] The training process maximizes the separation metric between disease positive and negative subjects. The high dimensional projection along with locations of extreme bins in the HDH's and all scaling/shifting information are stored for the inference process in which the training is applied to a new subject to determine disease status. The inference step is shown in **Error! Reference source not found.**.

[035] Temperature features from multiple Regions of Interest (ROI) on the face can be combined for the detection of or contribute to the classification of the state of human health including diseases such as but not limited to COVID-19, influenza, streptococcus, and respiratory syncytial virus.

[036] The ROI presented in **Error! Reference source not found.**. An image segmentation algorithm is used to extract mask images of the facial ROIs such as the cheeks, eyes, forehead, mouth, and nose.

[037] For each image, temperature data associated with each ROI mask is tabulated and analyzed for target features of interest. The array of temperature features including but not limited to means, variances, quartile, etc. are used for training as shown in **Error! Reference source not found.** and for inference as shown in **Error! Reference source not found.**.

[038] Temperature spatial gradients within individual ROIs on the face can be used for the detection of or contribute to the classification of the state of human health including such as but not limited to COVID-19, influenza, streptococcus, and respiratory syncytial virus.

[039] The purpose of this process is to measure the spatial structure inside individual ROIs in the face. The reasoning is that temperatures will be elevated differently inside a subject when they have COVID19, flu or other infection. For example, obtaining a temperature by scanning the forehead only gives partial information; fever can be caused by quite a number of causes. In addition, ambient temperature can also affect raw surface temperature readings of the forehead and the cheeks. However, these spatial gradients can still contain useful signs of various diseases.

[040] Spatially dependent temperature profiles are measured within each ROI. These profiles and resulting analysis of associated data provide features that are used for training as shown in **Error! Reference source not found.** and for inference as shown in **Error! Reference source not found.**.

[041] Spectral features extracted from hyperspectral images can be used for the detection of or contribute to the classification of the state of human health including diseases such as but not limited to COVID-19, influenza, streptococcus, and respiratory syncytial virus.

[042] The schematic of this procedure is shown in **Error! Reference source not found.** which shows a hyperspectral image of a mouth and the corresponding spectral intensity which can also be applied to the eyes or other regions of interest on the human body.

[043] In this embodiment the ROI is selected using a facial image segmentation algorithm on the central projection image. This is used to extract the region on the dispersed projection containing the spectral data associated with that ROI. This spectral data is then processed and interrogated for features such as locations of peaks, slopes in predetermined regions, and other features.

[044] This algorithm is not restricted to wavelengths in the visible range. While the visible range color is a good indicator for detection in certain cases, this approach can be applied to a wider range of wavelengths from the UV to long-range IR (LWIR). For blazed gratings used in the IR range, such a tool adds temperature analysis functionality from the corresponding spectra.

[045] A variety of optical elements could be utilized for the measurement of spectral information including wavelength specific features contained in an image. Such elements may include color filters or dispersive optical components, for example; a computer generated phase grating, holographic grating, prism, grism, or any other dispersive optical elements which could be tuned and utilized for different applications such as the direct detection of bacteria or viruses.

[046] Recorded images (visible, ultraviolet or infrared) of the face and or eyes can be used for the detection of or contribute to the classification of the state of human health including diseases such as but not limited to COVID-19, influenza, streptococcus, and respiratory syncytial virus by extracting features from blood vessels within the sclera and their immediate surroundings.

[047] In this embodiment visible image of the eye or eyes are pre-processed, and the blood vessels (and their surroundings) are segmented as shown in **Error! Reference source not found.**. These segments are sorted based on various features and combinations as shown in **Error! Reference source not found.**. Then, features from a number of blood vessels that are within the extremes of the sorted list are extracted and stored as candidate features for training. In

training, the features that contribute the most to separation between disease positive subjects and disease negative subjects are selected.

[048] High Dimensional Histograms (HDH) also result in features that will compete with others in training. HDH by themselves are not novel. However, the application HDH in the training and inference process is. Values in every bin in the HDH for a set of disease positive subjects is compared with a set of disease negative subjects. Bins that yield separation between these two classes are noted and participate in training and inference as features.

[049] Fusion of multiple independent sensor data to create an accurate health assessment that can detect diseases such as but not limited to COVID-19, influenza, streptococcus, and respiratory syncytial virus.

[050] Disease detection based on a single sensor is itself may not be specific to a particular condition. For example, many diseases present with an elevated temperature. However, a thermal image of a subject's face will yield temperature spatial gradients that could be different for different conditions.

[051] There are many approaches to data fusion; the simplest being an average of features from disparate sensors. In this claim, the particular fusion process involves high dimensional comparisons of several features simultaneously. The selection of a limited number of key features is performed in the training process as shown in **Error! Reference source not found.**. Features that best separate disease positive subjects from disease negative subjects are chosen and used in inference when a human subject is tested. The high dimensional approach behaves like a classical Bayesian classifier for example which computes the probability of an event given another event has occurred. The difference is that the high dimensional classifier computes a detection metric based on several variables simultaneously.

[052] Also provided herein is a method to reduce the number of training samples needed to automatically detect diseases that is also transparent to human interpretation and enhancement.

[053] Modern Artificial Neural Networks (ANN) can be trained to detect diseases using a wide variety of cameras and other sensors. However, ANNs require large numbers of training subjects for any reasonable level of specificity and sensitivity. Moreover, ANNs cannot be investigated if

diagnostics are required to determine why a detection failed to correctly classify a disease. This is because ANNs are a large collection of trained "weights" which are just numbers that cannot be mapped to a particular physical metric or pathology.

[054] The feature extraction and fusion process presented in this patent application are inherently transparent as all features leading to a result are saved. This allows for adjustments to be made if there are consistent inaccuracies under given circumstances.

[055] Also provided herein is an automated robotic system and process for aligning a multi-sensor suite with a human subject to collect multi-sensor data for assessing human health.

[056] In order to perform multi-sensor disease detection, a subject must stand, or sit, or be positioned in front of the system as shown in **Error! Reference source not found.**. The wide FOV **13** and narrow FOV **12** sensors send data in individual frames or in a continuous stream such as video to the computer **30** (**Error! Reference source not found.**). Representations of recorded image data is shown in **Error! Reference source not found.**. A heuristic face finding algorithm is used on the recorded data creating a bounding rectangle around the face in the top half of **Error! Reference source not found.**. The positioning system **20** may include visual and or audio cues for guiding human self-positioning such as a display, monitor or speaker. The positioning system **20** may consist of a robotic positioning system, that includes multi-axis positioning control such as a mechanized elevator **23** and a gimbal **22** with pan, and tilt motion control as shown in **Error! Reference source not found.** are automatically adjusted until the subject is located within a specified region of interest in the wide FOV imaging sensor. This will localize the eye in the narrow field of view sensor close enough so that the positioning system can be fine-tuned until the bounding rectangle from a feature detection finder is located within a specified region of interest as shown in the bottom half of **Error! Reference source not found.**. A similar process can be used to collect data from the spectral sensor **14** looking at the face, mouth, eye or specified region of interest.

[057] Also provided herein is a non-contact system consisting of an array of integrated sensors from a common frame or platform which can jointly measure human vital signs in conjunction with conducting disease detection. The sensor array includes at least one visible imaging sensor **12**, at least one infrared imaging sensor **11**, at least one spectral sensor **14**, at least one

light source **15**, and at least one electronic and software controller. This unique combination of sensors is able to measure a continuous time sequence of human vital signs including body temperature, respiratory pattern including inhalation and exhalation, respiratory rate, pulse rate, heart rate, blood oxygen ratio, blood flow and pressure for both systolic and diastolic measurements, height, and approximate weight.

[058] The multiple sensor dataset using feature extraction used for disease detection as described in this embodiment can also be used to measure human vital signs.

List of Reference Numbers

[059] **10** sensor head unit

[060] **11** thermal imaging sensor

[061] **12** narrow FOV visible or infrared imaging sensor

[062] **13** wide FOV visible or infrared imaging sensor

[063] **14** hyperspectral imaging sensor

[064] **15** light source

[065] **16** single LIDAR sensor

[066] **17** multiple LIDAR sensors

[067] **20** positioning system

[068] **22** gimbal

[069] **23** mechanized elevator

[070] **24** pan control

[071] **25** tilt control

[072] **30** computer

WHAT IS CLAIMED IS:

1. Apparatus for determining presence or absence of disease comprising: a sensor head unit comprising one or more light sources and one or more sensors; a processor adapted for communicating with the sensors and receiving from the sensors and further adapted for determining presence or absence of disease.

2. The apparatus of claim 1 further compromising a support for the sensor head unit, wherein the support has an elevator and means for tilting and turning the camera head unit and means for moving the cameras within the sensor head.

3. The apparatus of claim 1 wherein the sensors on the sensor head further comprise a LIDAR source and receiver adapted for determining the distance of a user's face from the camera head unit.

4. The apparatus of claim 1 wherein the sensors include a thermal imaging sensor.

5. The apparatus of claim 4 wherein the sensors in the sensor head unit further comprise
a movable wide field of view visible or infrared imaging sensor with a heuristic finder which is movable within a first boundary structure; and
a movable narrow field of view visible or infrared imaging sensor which is movable within a second boundary structure.

6. The apparatus of claim 5 further comprising a neural network eye finder connected to the narrow field of view imaging sensor.

7. The apparatus of claim 5 wherein the sensor head unit further comprises a hyperspectral imaging sensor.

8. The apparatus of claim 7 wherein the hyperspectral imaging sensor is movable.

9. The apparatus of claim 8 wherein the processor is adapted to process all information from the images of the thermal imaging sensor, the hyperspectral imaging sensor, and the visible eye images and to provide a health assessment score for a given disease.

10. The apparatus of claim 9 wherein the processor is adapted to compare the images of the sensors with sets of known histograms of positive and negative scores for the given disease.

11. A method of determining absence or presence of disease comprising
providing a sensor head unit comprising one or more light sources and one or more sensors;
providing a processor adapted for communicating with the sensors and receiving from the sensors;
providing sets of known histograms of positive and negatives of a given disease to the processor;
providing images from the sensors to the processor;
comparing the images from the sensors with the sets of known histograms in the processor; and
providing health assessments from the processor for the given disease.

12. The method of claim 11, wherein the step of providing the sensor head unit comprises providing a thermal imaging sensor, a wide field of view imaging sensor, a narrow field of view imaging sensor, and a hyperspectral imaging sensor.

13. The method of claim 12 further comprising providing a LIDAR sensor in the sensor head unit.

14. The method of claim 13 further comprising
relatively positioning the sensor head unit with a face of a human subject,
aligning the wide field of view imaging sensor with the face of the subject, and
aligning the narrow field of view imaging sensor with an eye of the subject.

15. The method of claim 14, further comprising
processing images of the eye of the subject by segmenting the images into iris and sclera,
creating visible or infrared images from the iris,
creating visible or infrared images from the sclera,
creating images with the hyperspectral imaging sensor, and
providing the created images to the processor.

16. The method of claim 15 further comprising creating from the hyperspectral imaging sensor images of blood vessels and their surroundings and providing those images to the processor.

17. The method of claim 11 further comprising providing thermal images of a forehead, eyes, nose, cheeks and mouth of the subject from the thermal imaging sensor to the processor.

18. The method of claim 11 further comprising providing images of an open mouth of a subject from the hyperspectral imaging sensor to the processor.

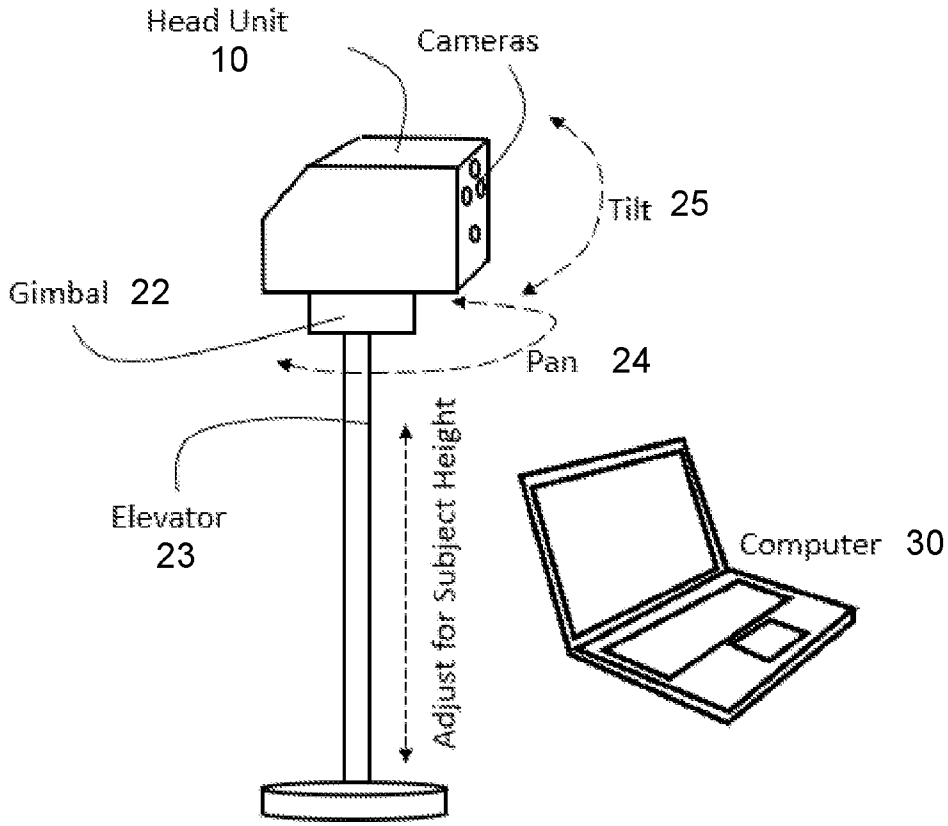
Head Unit
10
Cameras
Tilt 25
Gimbal 22
Pan 24
Elevator
23
Adjust for Subject Height
Computer 30

Figure 1

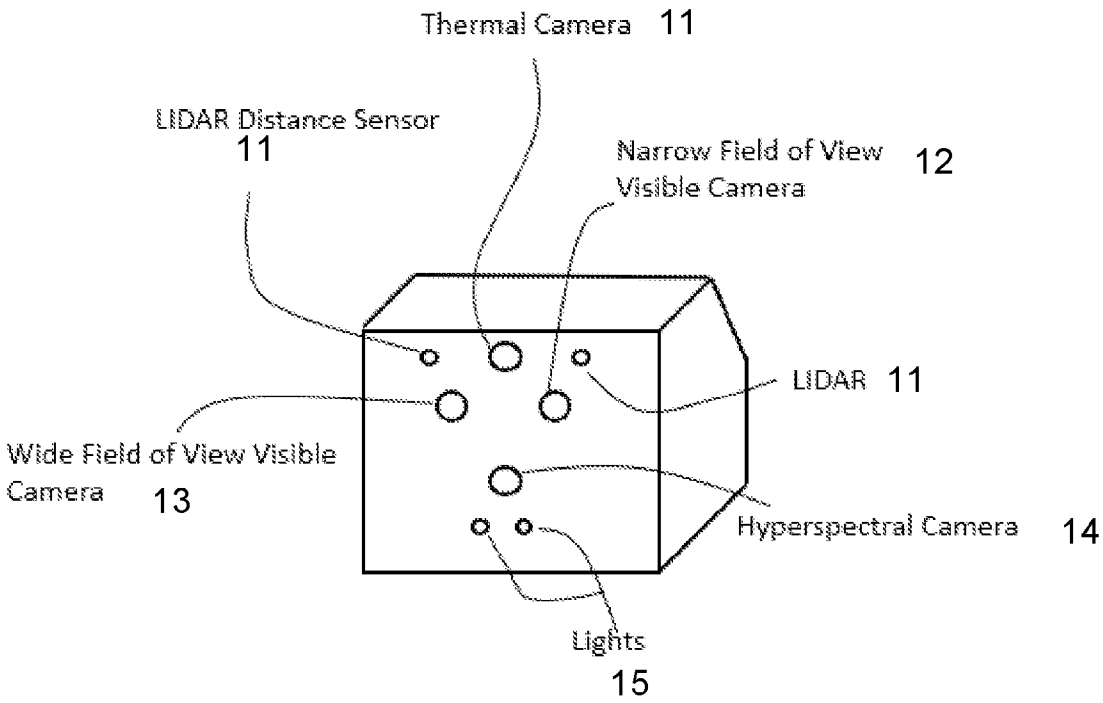
Thermal Camera 11
LIDAR Distance Sensor
11
Narrow Field of View
Visible Camera
12
LIDAR 11
Wide Field of View Visible
Camera
13
Hyperspectral Camera
14
Lights
15

Figure 2

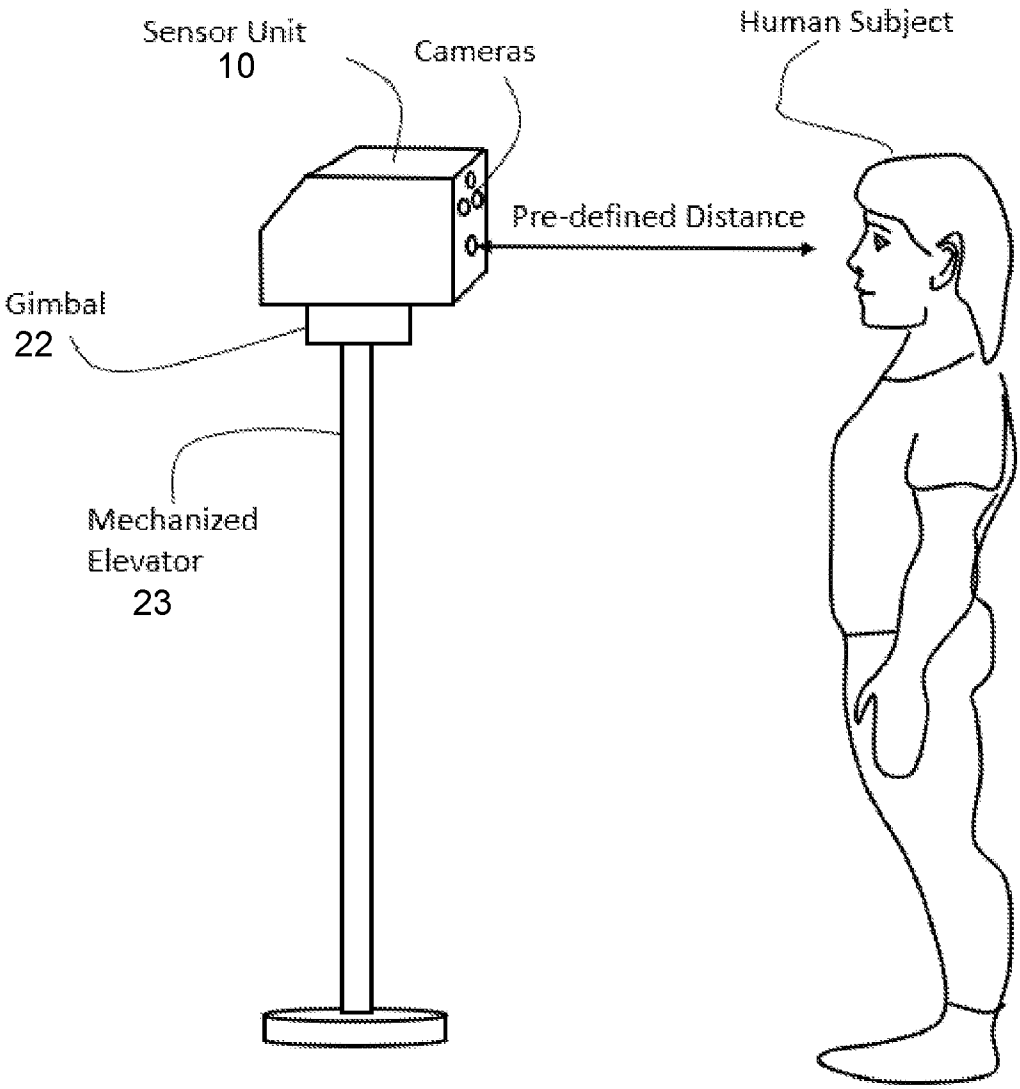
Sensor Unit
10
Cameras
Human Subject
Pre-defined Distance
Gimbal
22
Mechanized
Elevator
23

Figure 3

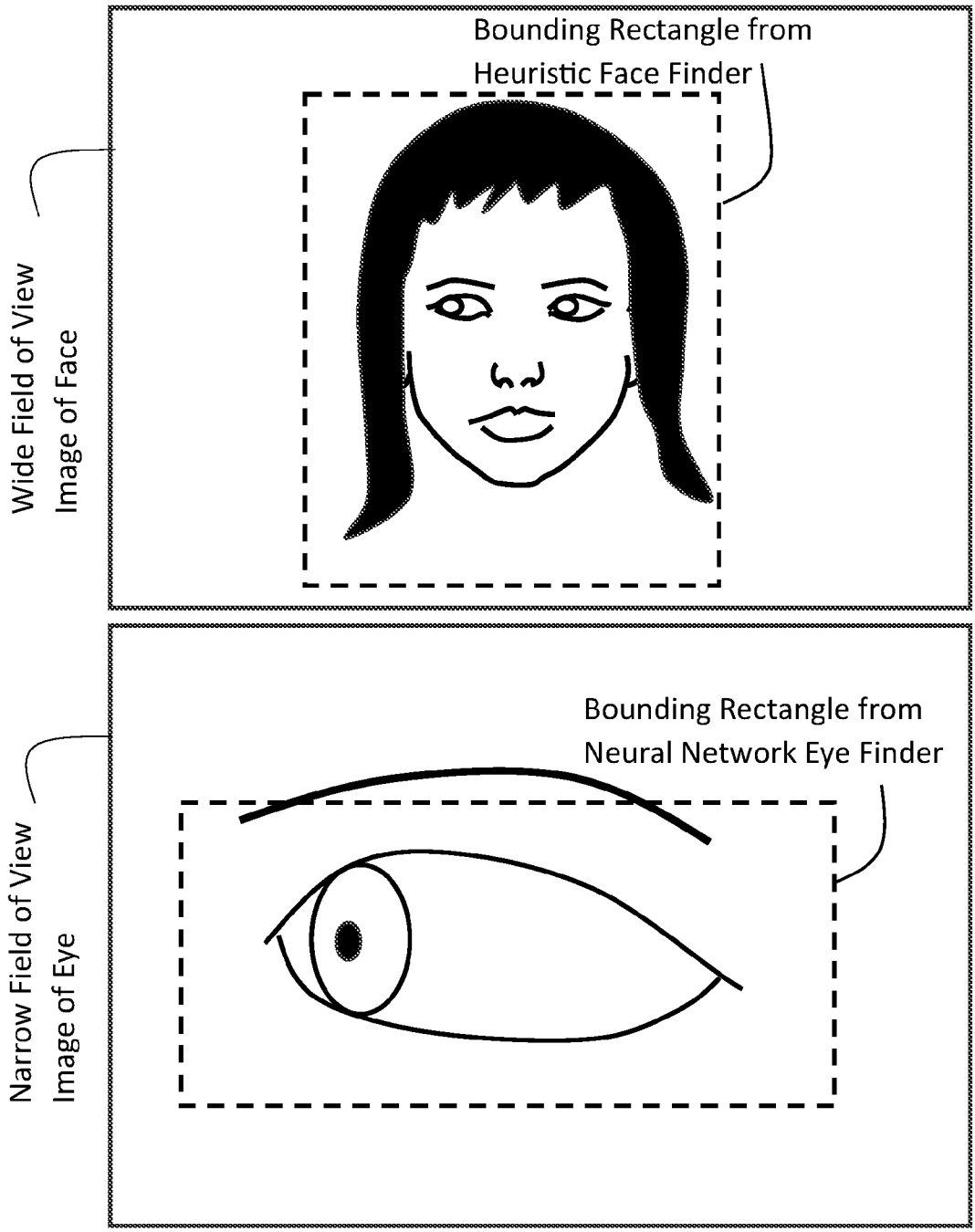
Bounding Rectangle from
Heuristic Face Finder
Wide Field of View
Image of Face
Bounding Rectangle from
Neural Network Eye Finder
Narrow Field of View
Image of Eye

Figure 4

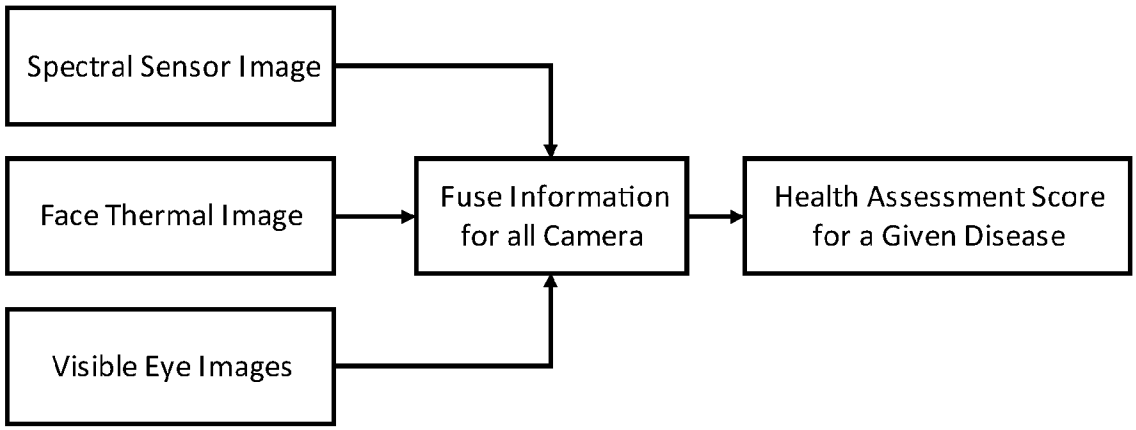
Spectral Sensor Image
Face Thermal Image
Visible Eye Images
Fuse Information for all Camera
Health Assessment Score for a Given Disease

Figure 5

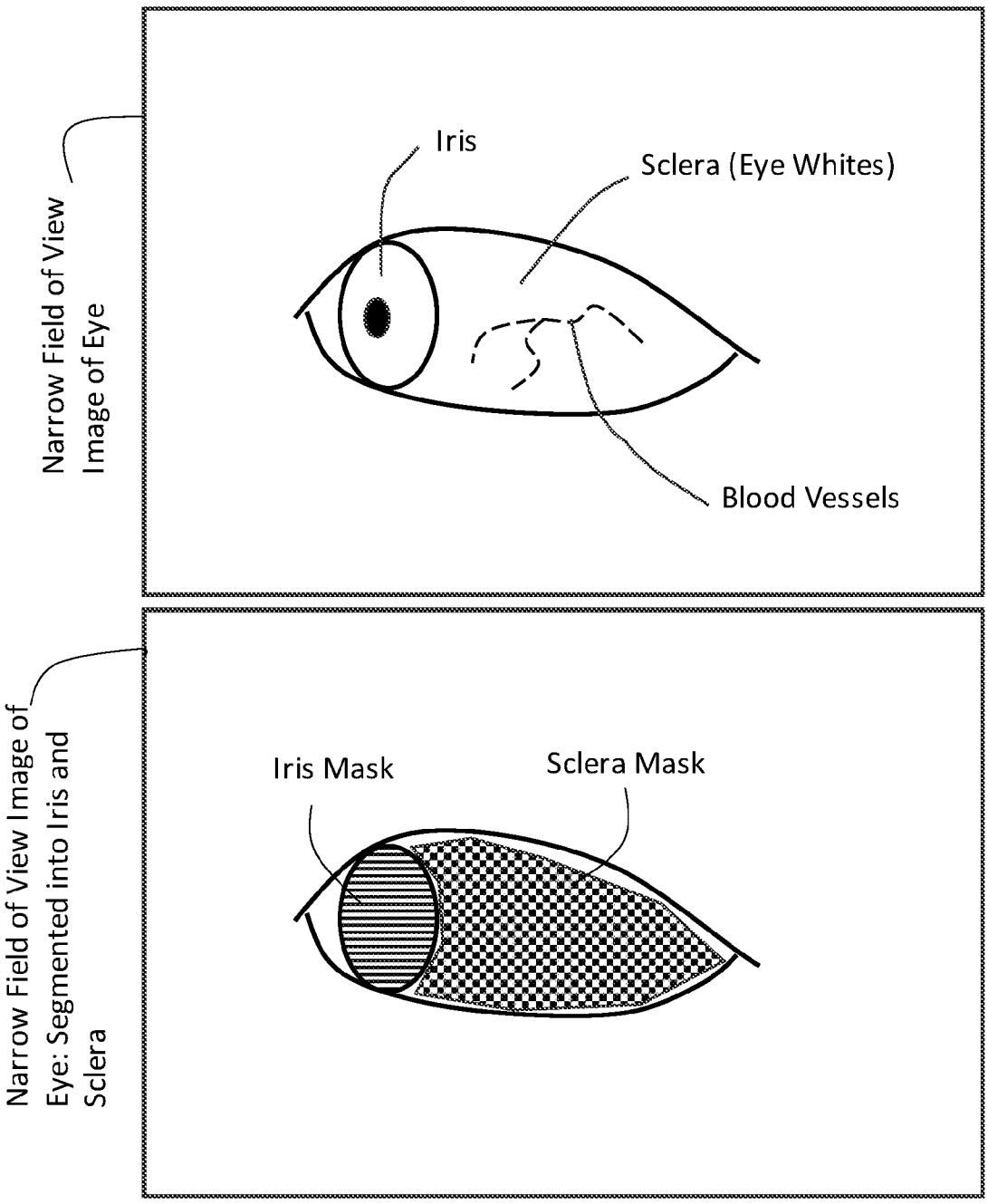
Narrow Field of View Image of Eye
Iris
Sclera (Eye Whites)
Blood Vessels
Narrow Field of View Image of Eye: Segmented into Iris and Sclera
Iris Mask
Sclera Mask

Figure 6

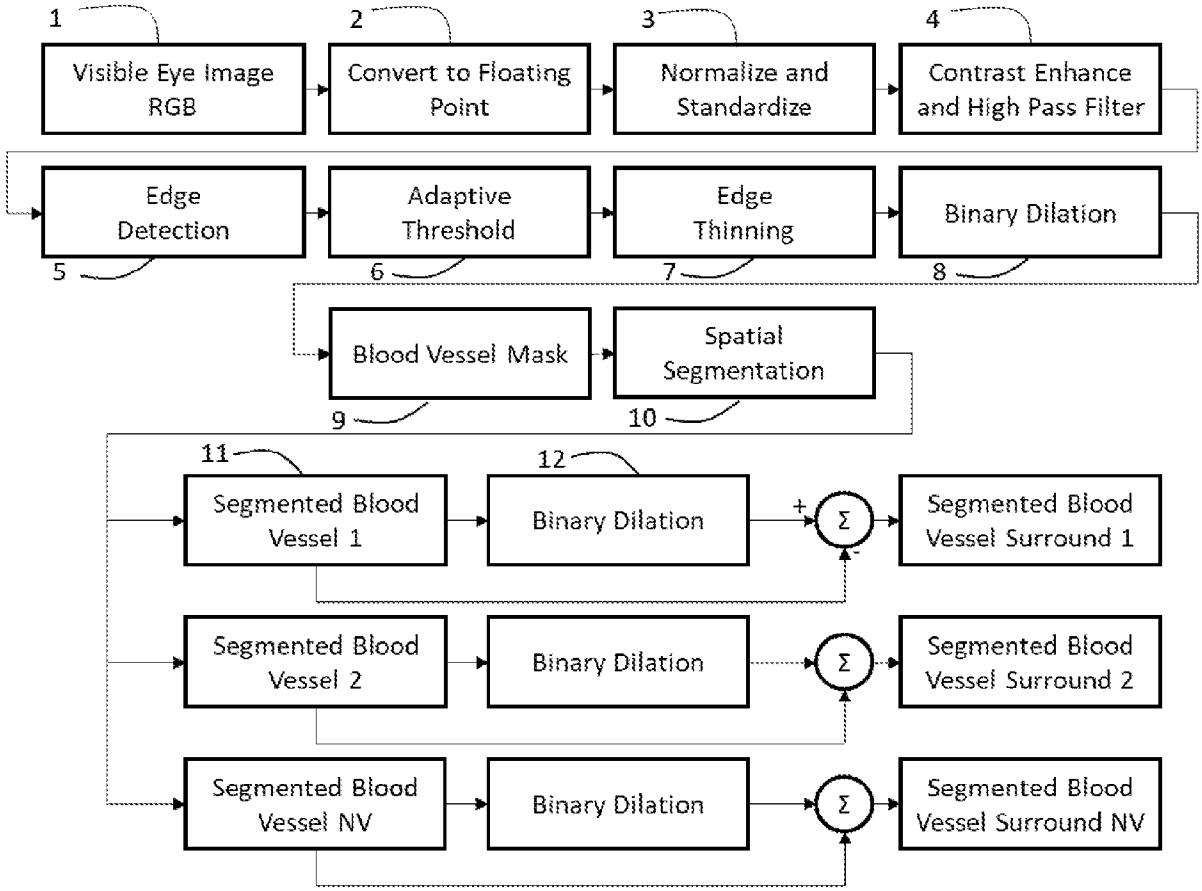
1
Visible Eye Image RGB
2
Convert to Floating Point
3
Normalize and Standardize
4
Contrast Enhance and High Pass Filter
Edge Detection
5
Adaptive Threshold
6
Edge Thinning
7
Binary Dilation
8
Blood Vessel Mask
9
Spatial Segmentation
10
11
Segmented Blood Vessel 1
12
Binary Dilation
+
Σ
-
Segmented Blood Vessel Surround 1
Segmented Blood Vessel 2
Binary Dilation
Σ
Segmented Blood Vessel Surround 2
Segmented Blood Vessel NV
Binary Dilation
Σ
Segmented Blood Vessel Surround NV

Figure 7

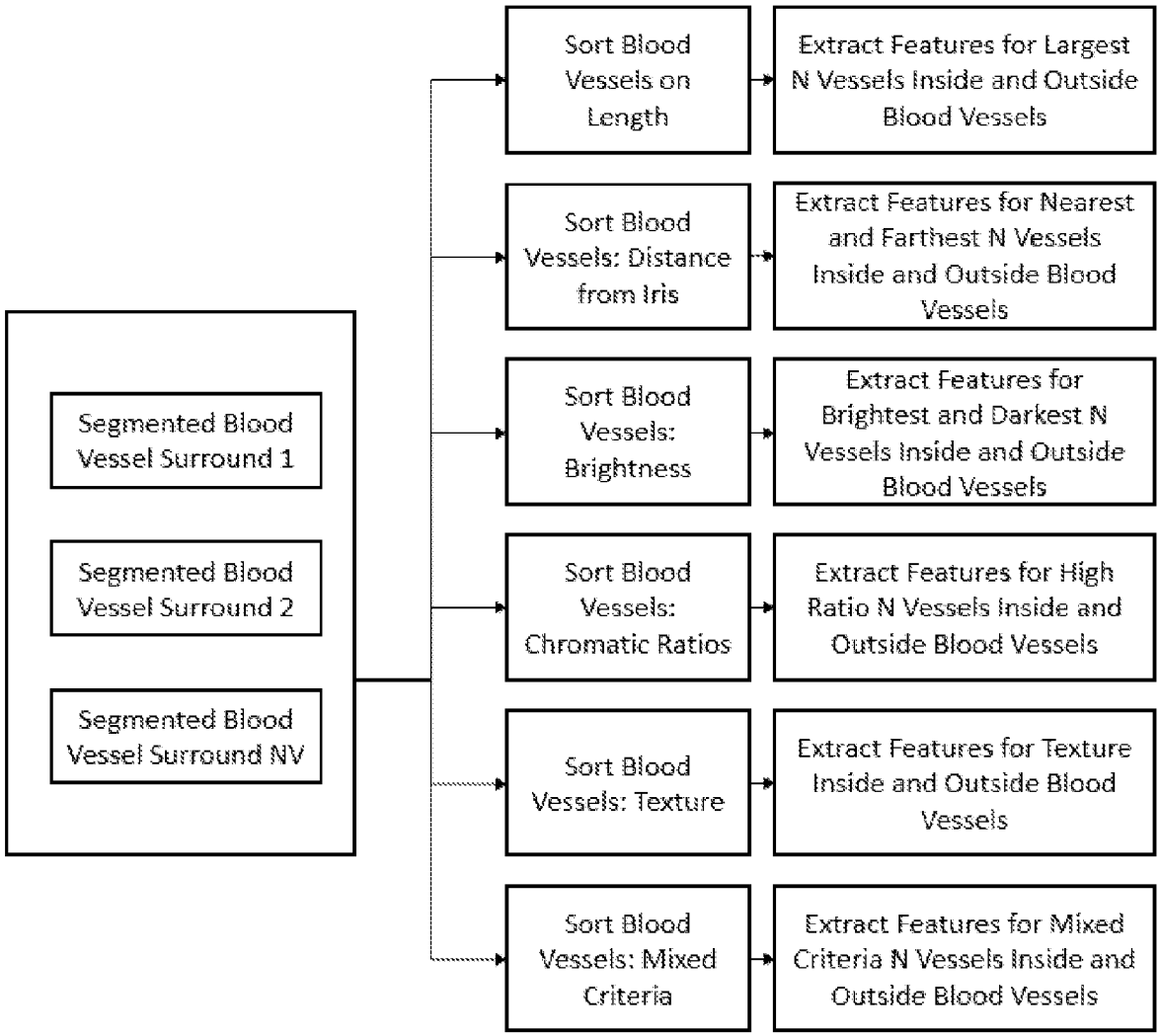
Segmented Blood Vessel Surround 1
Segmented Blood Vessel Surround 2
Segmented Blood Vessel Surround NV
Sort Blood Vessels on Length
Extract Features for Largest N Vessels Inside and Outside Blood Vessels
Sort Blood Vessels: Distance from Iris
Extract Features for Nearest and Farthest N Vessels Inside and Outside Blood Vessels
Sort Blood Vessels: Brightness
Extract Features for Brightest and Darkest N Vessels Inside and Outside Blood Vessels
Sort Blood Vessels: Chromatic Ratios
Extract Features for High Ratio N Vessels Inside and Outside Blood Vessels
Sort Blood Vessels: Texture
Extract Features for Texture Inside and Outside Blood Vessels
Sort Blood Vessels: Mixed Criteria
Extract Features for Mixed Criteria N Vessels Inside and Outside Blood Vessels

Figure 8

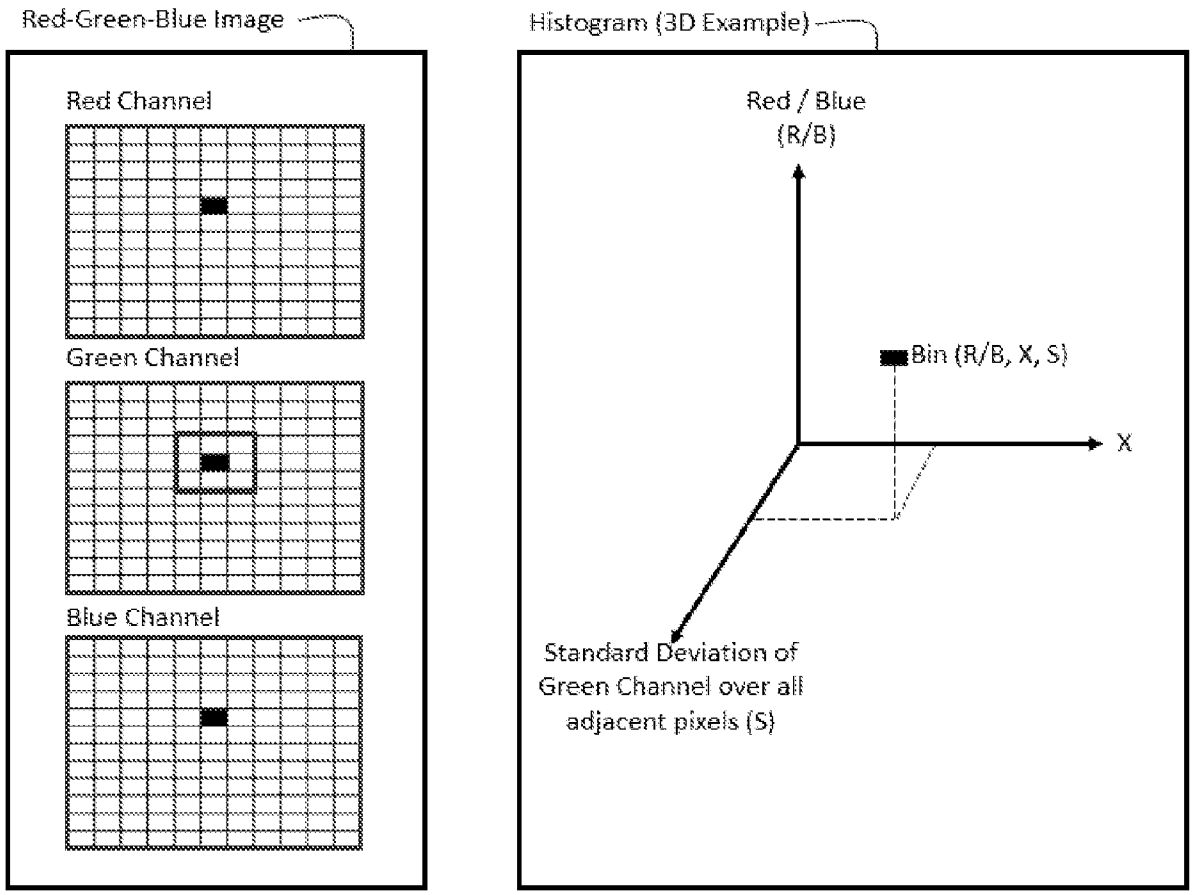
Red-Green-Blue Image
Red Channel
Green Channel
Blue Channel
Histogram (3D Example)
Red / Blue
(R/B)
Bin (R/B, X, S)
X
Standard Deviation of
Green Channel over all
adjacent pixels (S)

Figure 9

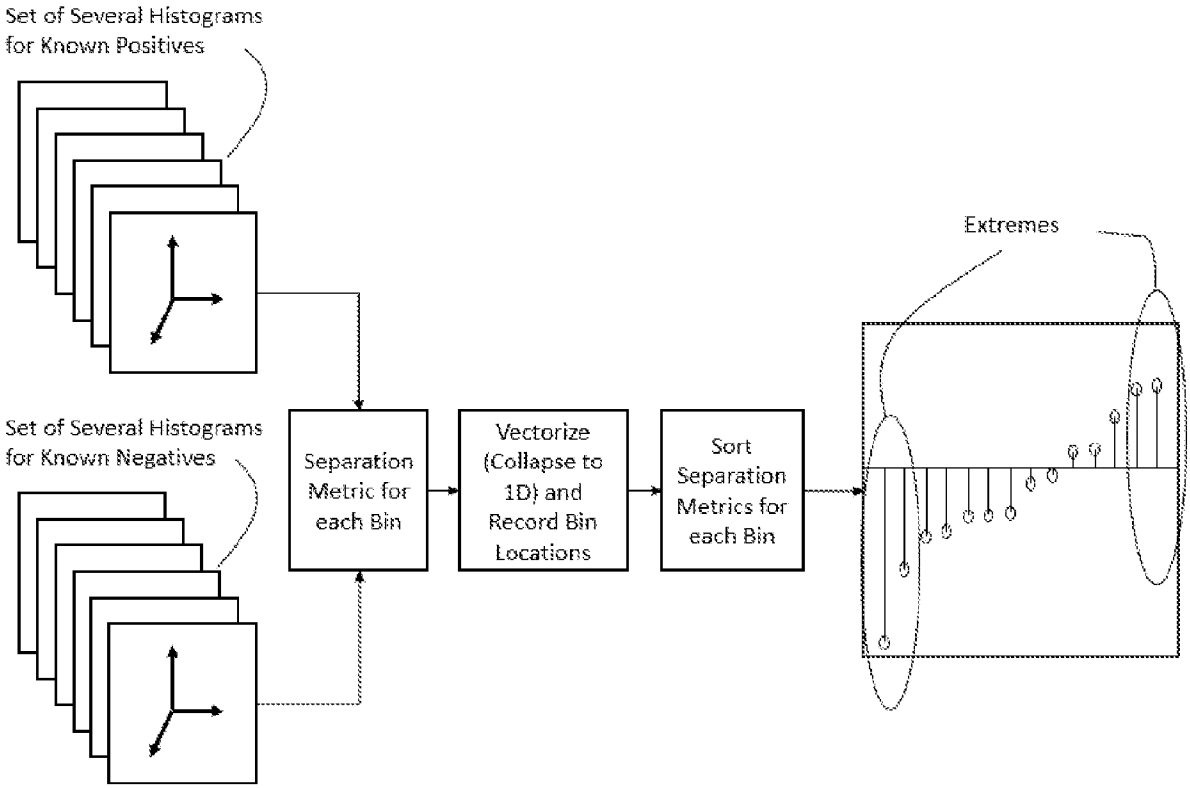
Set of Several Histograms for Known Positives
Set of Several Histograms for Known Negatives
Separation Metric for each Bin
Vectorize (Collapse to 1D) and Record Bin Locations
Sort Separation Metrics for each Bin
Extremes

Figure 10

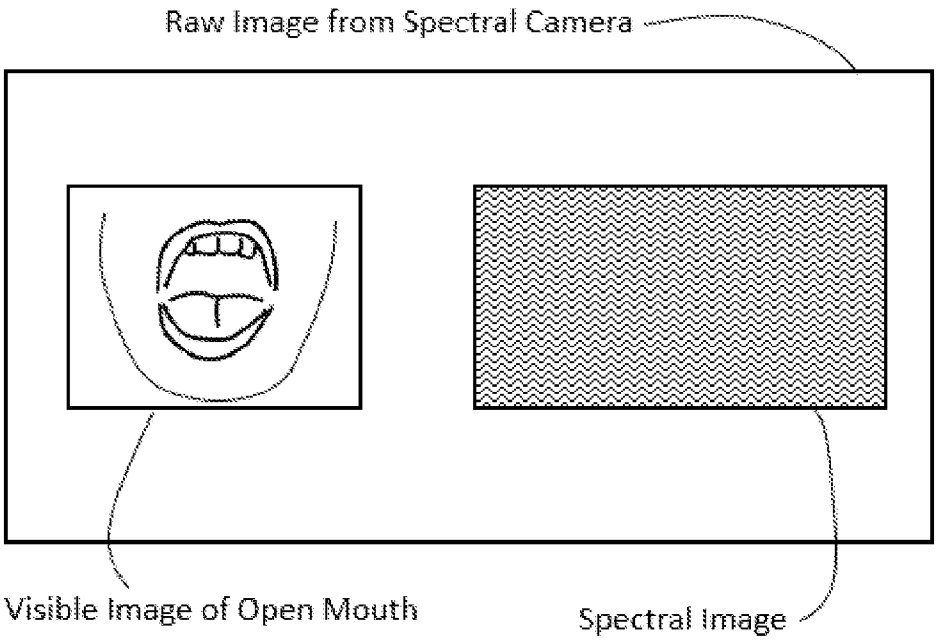
Raw Image from Spectral Camera
Visible Image of Open Mouth
Spectral Image

Figure 11

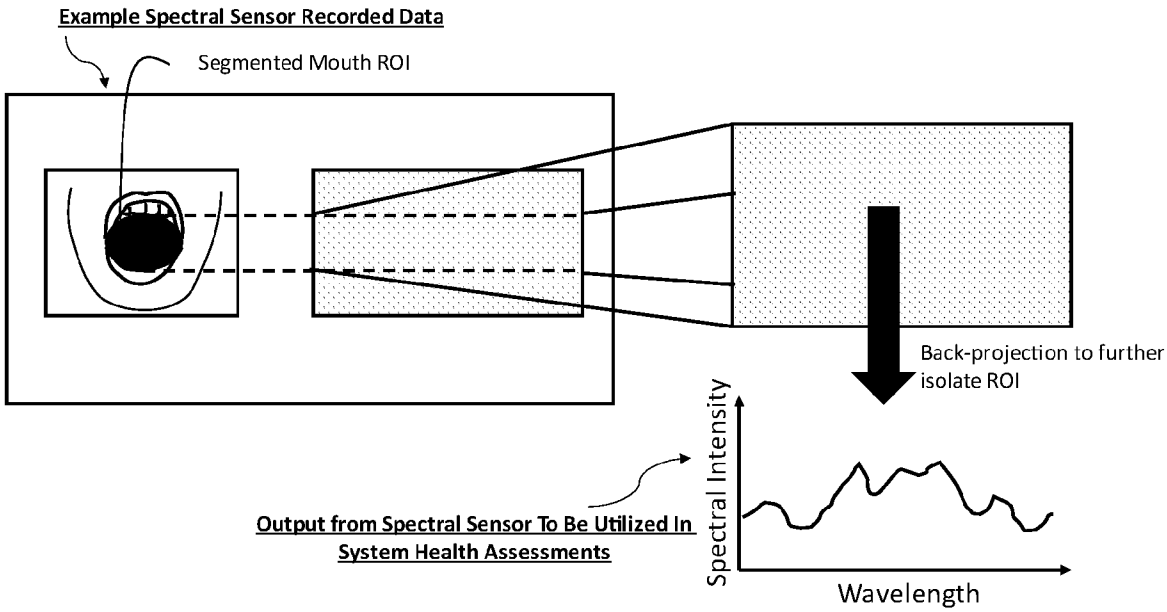
Example Spectral Sensor Recorded Data
Segmented Mouth ROI
Back-projection to further isolate ROI
Output from Spectral Sensor To Be Utilized In System Health Assessments
Spectral Intensity
Wavelength

Figure 12

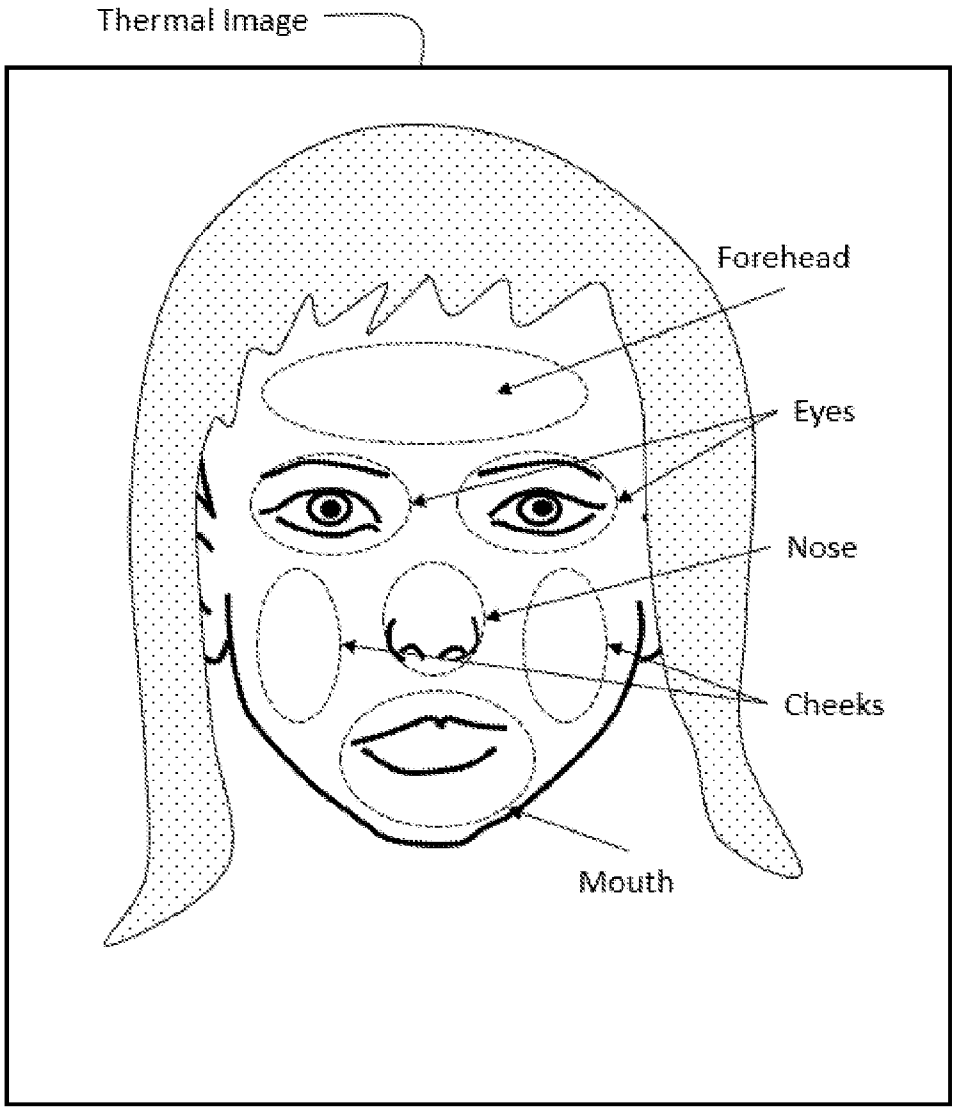

Figure 13

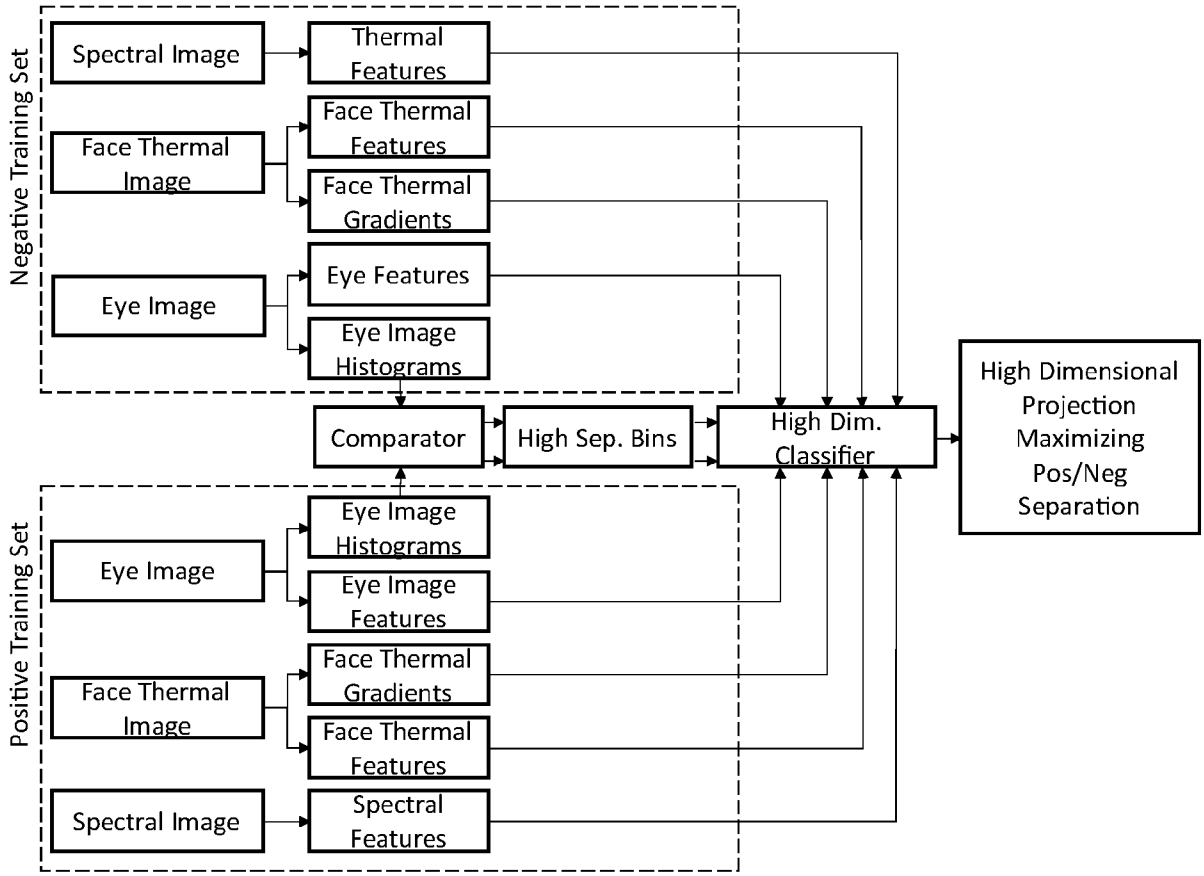
Negative Training Set
Spectral Image
Thermal Features
Face Thermal Image
Face Thermal Features
Face Thermal Gradients
Eye Image
Eye Features
Eye Image Histograms
Comparator
High Sep. Bins
High Dim. Classifier
High Dimensional Projection Maximizing Pos/Neg Separation
Positive Training Set
Eye Image
Eye Image Histograms
Eye Image Features
Face Thermal Image
Face Thermal Gradients
Face Thermal Features
Spectral Image
Spectral Features

Figure 14

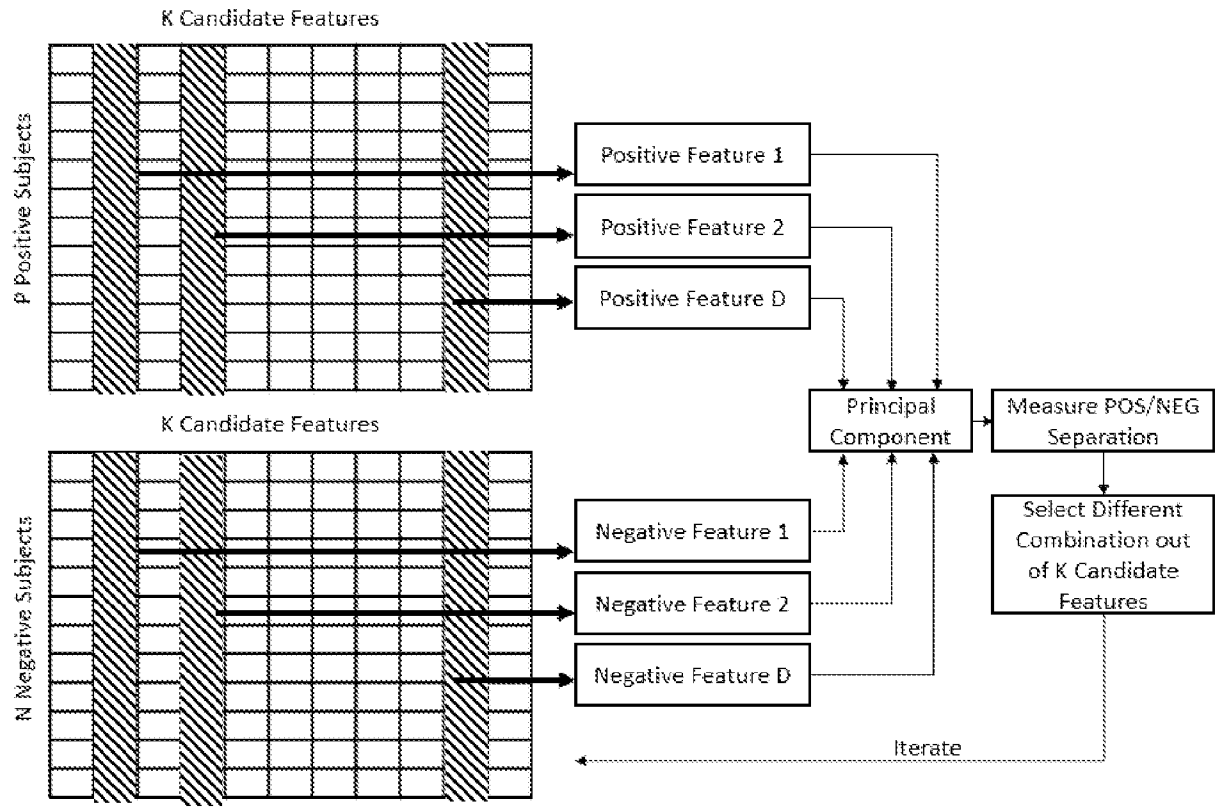
K Candidate Features
P Positive Subjects
Positive Feature 1
Positive Feature 2
Positive Feature D
K Candidate Features
N Negative Subjects
Negative Feature 1
Negative Feature 2
Negative Feature D
Principal Component
Measure POS/NEG Separation
Select Different Combination out of K Candidate Features
Iterate

Figure 15

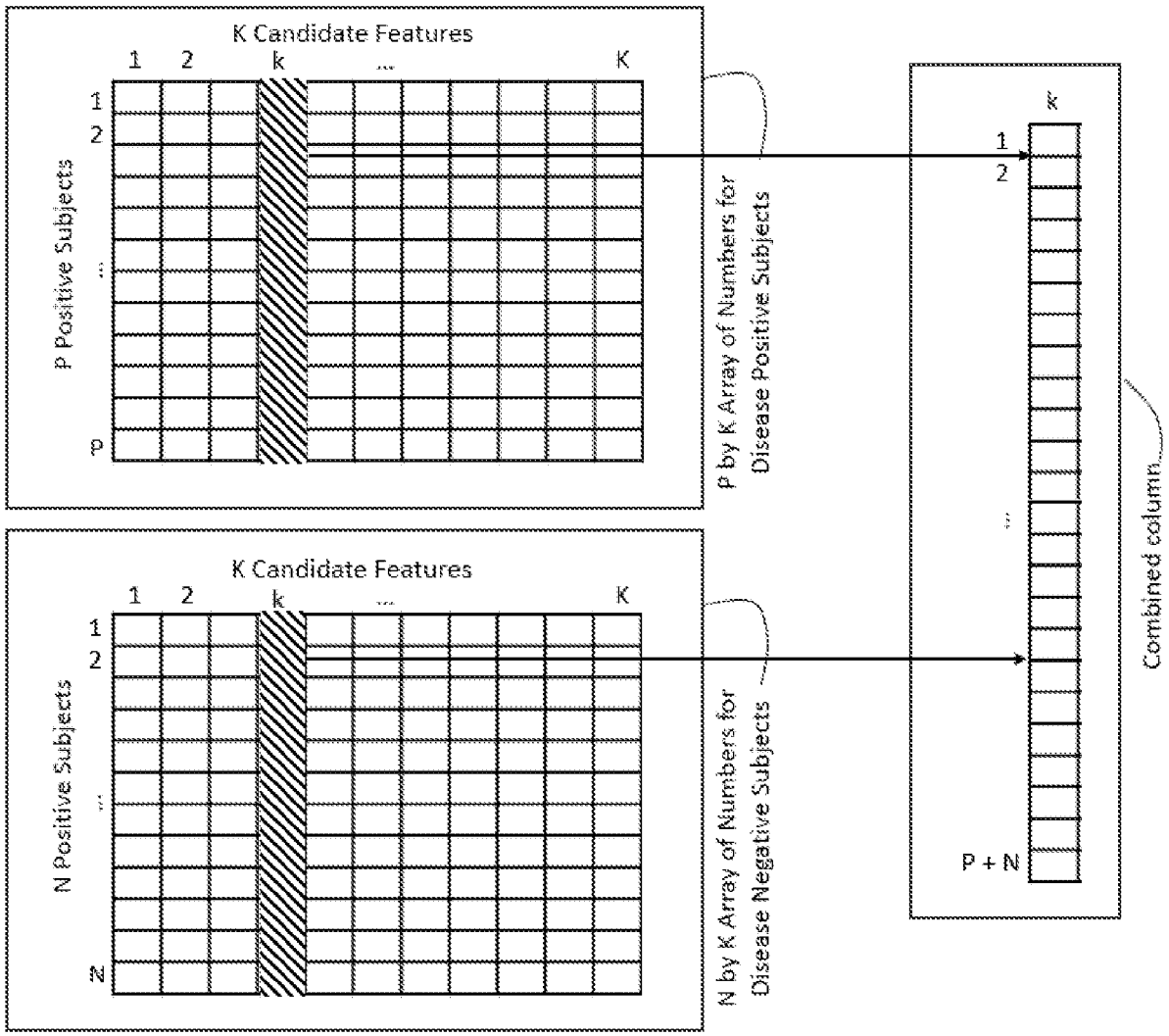
K Candidate Features
1
2
k
...
K
1
2
...
P
P Positive Subjects
P by K Array of Numbers for Disease Positive Subjects
K Candidate Features
1
2
k
...
K
1
2
...
N
N Positive Subjects
N by K Array of Numbers for Disease Negative Subjects
K
1
2
...
P + N
Combined column

Figure 16

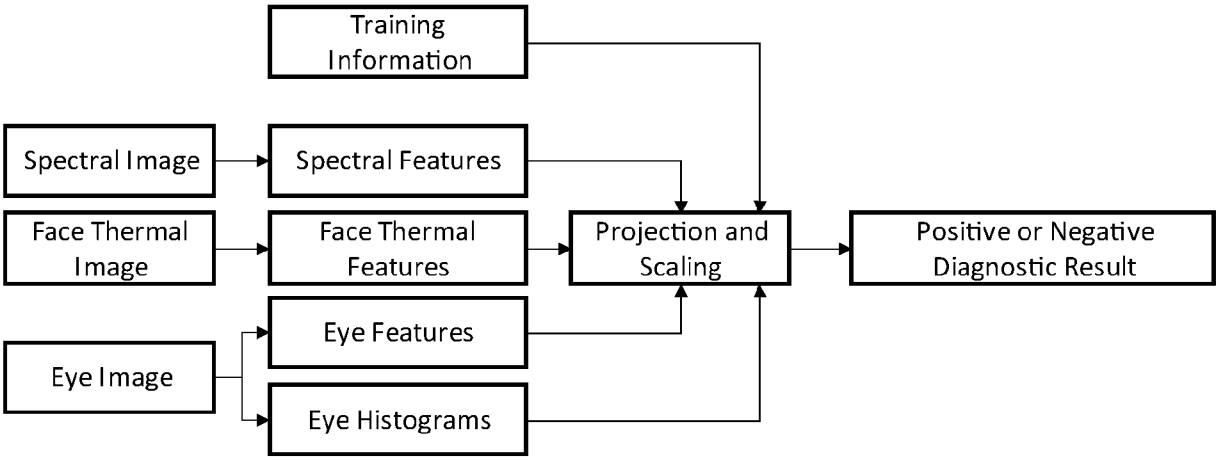
Training Information
Spectral Image
Spectral Features
Face Thermal Image
Face Thermal Features
Projection and Scaling
Positive or Negative Diagnostic Result
Eye Features
Eye Image
Eye Histograms

Figure 17