Efficient Eye Location for Biomedical Imaging using Two-level Classifier Scheme

Mi Young Nam, Xi Wang, and Phill Kyu Rhee*

Abstract: We present a novel method for eye location by means of a two-level classifier scheme. Locating the eye by machine-inspection of an image or video is an important problem for Computer Vision and is of particular value to applications in biomedical imaging. Our method aims to overcome the significant challenge of an eye-location that is able to maintain high accuracy by disregarding highly variable changes in the environment. A first level of computational analysis processes this image context. This is followed by object detection by means of a two-class discrimination classifier (second algorithmic level).We have tested our eye location system using FERET and BioID database. We compare the performance of two-level classifier with that of non-level classifier, and found it's better performance.

Keywords: Biomedical imaging, eye location, two-level classifier, image context.

1. INTRODUCTION

This into image-guided intervention therapy is currently focused on problems of locating and recognizing tissues and objects of interest during surgery and on real-time monitoring of therapy. Imaging technologies have become increasingly accurate, offering higher resolution and efficiency and, as biomedical image analysis plays an important role in areas of clinical diagnosis, image technology has drawn intense from scientists and physicians [1]. Images of the eye are widely used in the diagnosis and treatment of various eye diseases such as Diabetic Retinopathy and glaucoma [2-4]. Diagnosis and treatment of such eye diseases is greatly assisted by computer analysis of images to locate the eye and pupil with high accuracy. Moreover, equipment to support both such medical diagnoses and studies of human balance in real-time is under development [5]. The eye is sensitive to contact with any external agent however, and diagnostic equipment that touches the eye cannot obtain precise data owing to the resistance offered by the eye's reflex. How to circumvent or overcome this is a challenge. The modest contribution of this study is an eye location method by means of a two-level classifier scheme. Its intended use is to assist with the diagnosis of eye diseases.

In the real world, there is a close connection between objects and a set of environments where those objects are usually found. One can exploit this connection to improve the accuracy and efficiency of a detection system. With this in mind, a two-level classifier that will behave in a robust manner under such variations of input image data is proposed here. The algorithm will be addressed in a later section. The first level of the proposed classifier scheme consists of an image context analysis. The image context analysis has two stages with different objectives: clustering in the training phase and identification in the testing phase. The main goal of the second level of the two-level classification system is to assign the image data into one of two categories: the target object, and everything else. The total system therefore consists of context clustering and object detection.

Context clustering in the first level may be done by an unsupervised learning method such as self organizing memory (SOM) or k-means clustering. Context identification may be implemented by a classification method such as neural network (NN) or K- Nearest Neighbor (K-NN). Identification or detection in the second level is a combination scheme using multiple classifiers that aims to produce superiority over schemes using a single classifier in terms of accuracy and reliability [6].

The multiple classifiers combination approach is popular in the literature [9,10]. In the proposed scheme, individual candidate classifiers that depend on the output from the first level are activated in parallel. Their task is object detection. During the task of it performs false detection elimination that removes

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false detections from the result of each individual classifier. In the classifier fusion process, it combines output of the classifiers to achieve an optimal classification result.

The proposed method has been tested using two data sets and their virtual data sets (the FERET and BioID databases) where facial images are exposed to different lighting conditions. The proposed system achieves encouraging experimental results, with performance that is superior to that of popular alternate methods.

The organization of this paper is as follows. Problem identification, literature review and back ground work are discussed in Sction 1. Section 2 of this paper introduces the structure of the proposed eye location system using the experimental two-level classifier scheme. This is followed with a presentation of the objective and makeup of the first-level classifier and the second-level classifier (Sctions 3 and 4). Results are presented in Sction 5 showing the performance of the proposed eye location system. Finally Sction 6 concludes based on our research findings.

2. EFFICIENT EYE LOCATION USING TWO-LEVEL CLASSIFIER SCHEME

In this section, the outline of the proposed scheme is described. As the title suggests, a two-level classifier scheme consists of two levels, and each level has different objectives and objects of the classification when applied as part of an eye location system. Fig. 1 shows an overview of the eye location system with this two-level classifier scheme.

The first level performs image clustering during training and identification for testing purposes. In training, this level aims to cluster of image based on image context. In this paper, context represents various configurations, dynamic task requirement, application conditions, environmental conditions, etc. For the proposed eye-location application, changing illumination is the overwhelmingly important factor. In testing, multiple clusters with characteristics similar to those of the given context were used as the candidate clusters. Multiple clusters were used as candidates because the method used for identification may not be sufficiently robust to determine a single cluster that is closest to the true situation. In response, the system was designed to be adaptive to the varying illumination conditions.

The second-level classifier is based on the object detection or two-class method: discriminate a class of objects from all other background objects. Many such object detectors are implemented with a Support Vector Machine (SVM) [7], Naïve Bayes (NB) [8], and some other methods based on these, as described in [9,10]. An improved Bayesian classifier was used

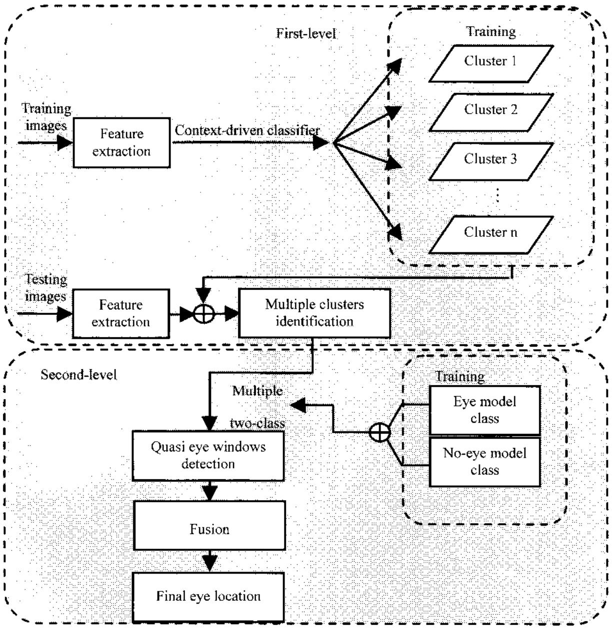

Fig. 1. The two-level classifier scheme applied to the eye location system.

as the main classifier in the second-level of the proposed system. A multiple Bayesian classifier undertakes eye detection. As a consequence, a sufficient number of eye images and of non-eye images is needed to train this Bayesian classifier. In this task, the varying illumination conditions are the destabilizing factor that must be focused on. The Bayesian classifiers in the second level must depend on the multiple clusters candidates that are obtained in the first level. In this sense, these classifiers may also be called multiple Bayesian classifiers. The final step in this level is optimally fusing the result from each candidate Bayesian classifier to obtain the eye location. Such a two-level classifier scheme is expected to produce superior performance to that of a single classifier scheme in terms of accuracy and reliability.

3. FIRST-LEVEL CLASSIFIER: CONTEXT-DRIVEN CLUSTERING AND IDENTIFICATION

Fig. 2 shows the structure of the first level. In the process of training in this first-level, the root node represents the training images and the child nodes represent the image clusters with common attributes. A large number of training images that typify different properties are used. In the testing process, the root node indicates the images that need testing and the child nodes are images already chosen during training. The selection of a proper cluster that is most likely to produce an accurate output for the current environment of a given image is next attempted.

In training, the task of the first level is clustering,

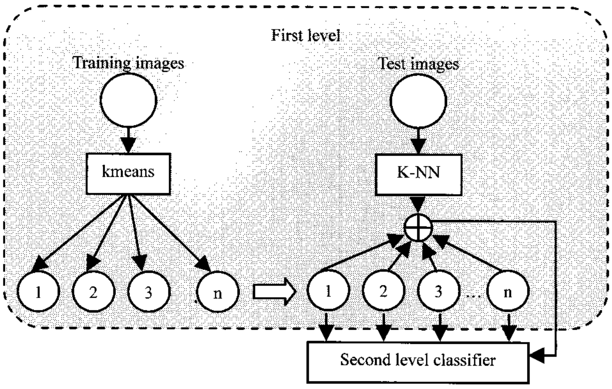

Fig. 2. The structure of the proposed first level classifier.

which depends on the image context analysis. An unsupervised clustering algorithm k-means [11] is adopted so that the proposed system may account for varying illumination. The procedure follows a simple and easy method to classify a given data set through a certain number of clusters that are fixed a priori. The algorithm is composed of the following steps:

A. Place K points into the space represented by the objects that are being clustered. These points represent initial group centroids.
B. Assign each object to the group that has the closest centroid.
C. When all objects have been assigned, recalculate the positions of the K centroids.
D. Repeat steps (b) and (c) until the centroids no longer move. This produces a separation of the objects into groups from which the metric to be minimized can be calculated.

In testing, the image context analysis assigns detected face images or manually arranged face images into image categories. Because of complex background or illumination conditions, sometimes an image cannot be classified into just one cluster. In response to this issue, a strategy of multiple candidate clusters that collects categories with properties similar to those of the input image as candidates is employed. In the proposed eye location system, K-nearest neighbor [12] is employed for this task. K-nearest neighbor is a supervised learning algorithm where the result of a new instance query is classified based on the majority of K-nearest neighbor categories. The purpose of this algorithm is to classify a new object based on attributes and training datasets. The two-candidate cluster and three-candidate cluster schemes were used for testing, and the experimental results can be found in Section 5.

4. SECOND-LEVEL CLASSIFIER: ADAPTIVE EYE DETECTION

In this level, individual classifiers act with different thresholds, but with the same Bayesian principle

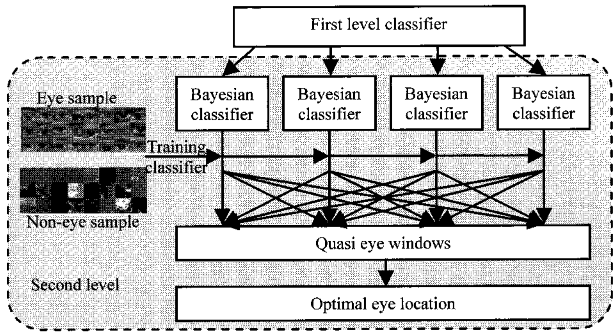

Fig. 3. The structure of second-level classifier.

discriminant. Fig. 3 illustrates the outline of this second level. After identification of candidate-clusters in the first level, the corresponding Bayesian classifiers are indicated to perform object detection using different thresholds. The classifier outputs in the first level can be treated as entrance to the second level. Two classes must be modeled for the Bayesian classifier. The object class should be modeled first, followed by modeling ofthe non-object class. In the proposed eye locationsystem, the eye is the target object.

A large number of eye images are extracted from each cluster and normalized to 16×16 pixels. Non-eye images are randomly extracted from the cluster. Fig. 4 shows an example of eye and non-eye image extraction. Blue regions indicate areas that are extracted as eye images and red regions are extracted as non-eye images.

4.1. Modeling eye and non-eye classes

With respect to this eye location system, one class is the eye class and the other is the non-eye class. In order to tolerate the change of illumination suitable for varying environments, multiple Bayesian classifiers are applied in this level. These multiple candidates Bayesian classifiers are relative to the candidate clusters that are decided in the first level.

These multiple Bayesian classifiers can be described by an ordered triplet data model that is defined as B= (F, E, N), where F={f1,...fn} is a set of clusters of face images, E={e1,...en} is the eye class model for Bayesian classifier, and N={n1,...nn} is the non-eye class model for the Bayesian classifier. The eye class model, ei, consists of eye images extracted from face images in cluster i. The non-eye class model, ni, consists of non-eye images extracted from face images in cluster i.

ω_{ei} is the posterior probability density of the eye class of cluster i. It is modeled as a normal distribution [13]:

$$p(x \mid \omega_{ei}) = \frac{1}{(2\pi)^{n/2} \mid \Sigma \mid^{1/2}}$$

$$\cdot \exp\{-\frac{1}{2}(x-M_e)^t \Sigma_e^{-1}(x-M_e)\}, \quad (1)$$

where M_e and Σ_e are the mean and the covariance matrix of the eye images respectively. The covariance matrix Σ_e can be factorized by principal component analysis (PCA) to give:

$$\Sigma_e = E_i R_i E_i^t \quad (2)$$

$$E_i E_i^t = diag\{\lambda_1, \lambda_2, ..., \lambda_n\}, \quad (3)$$

where E_i is an orthogonal eigenvector matrix, R_i is a diagonal eigenvalue matrix with diagonal elements i.e., eigenvalues, in dwindling order $(\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_n)$. A significant attribute of PCA is its optimal signal decomposition in the sense of lowest mean-square error when only a subset of principal components is used to depict the earlier signal. Vector X specifies the principal components:

$$X = E_i^t(x - M_e). \quad (4)$$

The components of X are the principal components. Applying the optimal signal decomposition attribute of PCA, only the first m $(m << n)$ principal components are used to estimate the posterior density function. Some of the training images used to construct the eye class model are shown in Fig. 4.

Practically any image can be offered as a non-eye sample because the domain of non-eye samples is much wider than the domain of eye examples. However, selecting a "representative" set of non-eye samples is a troublesome task. An ideal situation would be if the non-eye samples were similar to eyes but not. The non-eye class modeling starts by extracting non-eye samples that do not contain the whole eye region (see the red region of Fig. 3). Then, "representative" non-eye samples are generated by applying equation (4) to the extracted images. Those representative samples that lie closest to the eye class

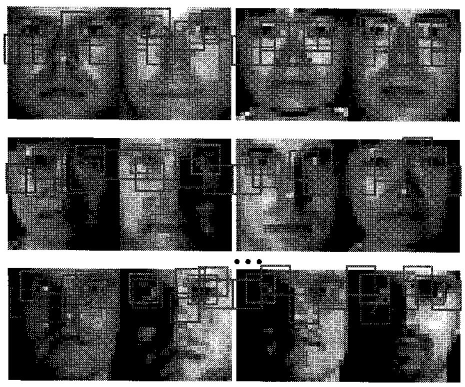

Fig. 4. Extraction of eye and non-eye images from cluster training data.

are chosen as modeling samples for the estimation of the posterior density function of the non-eye class, which is also modeled in a manner similar to that of the eye class. In Fig. 4 Squares with blue lines are eye region and squares with red lines are non-eye region.

4.2. Discriminate method in the second level

In order to signify the presence or absence of an eye, the associated multiple Bayesian classifiers that have two models made up of an eye model and non-eye model are applied for eye detection. The eye class and non-eye class models have been constructed as described above. The discriminate method in second level employs the Mahalanobis distance instead of the Euclidean distance. The Mahalanobis distance from a group of values with a mean m=(m1,m2,m3,...,mn) and covariance matrix $\sum$ for a multivariate vector I=(I1,I2,I3,...,In) is defined as[15]:

$$d(x) = \sqrt{(x-m)^t \sum^{-1}(x-m)}. \quad (5)$$

For the multiple candidates Bayesian classifier, let di(x)e be the Mahalanobis distance between the pattern of the region of interest and the eye class of cluster i, and di(x)n be the non-eye class of cluster i. The distances di(x)e and di(x)n can be computed from the input pattern x. The two thresholds θ and τ are used for classification. Their definitions are shown below:

$$\begin{aligned} \theta &= \max(d_i(E(x))_e), \\ \tau &= \max(d_i(N(x))_e - d_i(N(x))_n). \end{aligned} \quad (6)$$

In the above, $E(x)$ and $N(x)$, respectively, are the patterns of the training sample images of the eye and non-eye classes separately. The two thresholds are computed during training. The classification rule shown below is used to detect the eye in the system. We define the classification rule as:

$$x \in \begin{cases} \omega_e & \text{if } d(x)_e < \theta \text{ and } d(x)_e + \tau < d(x)_n \\ \omega_n & \text{otherwise} \end{cases} \quad (7)$$

The Bayesian classifier has some invariance to position and scale, which results in multiple windows around both an eye's correct and false locations. To address this issue, the next process focuses on removing the false location and fuses the multiple quasi results into an optimal eye location.

4.3. Deciding the optimal eye location

The second stage in the proposed second level is a resolution method that decides the optimal location of the eye from among the multiple candidate locations. The strategy in this process has two parts: Elimination and Fusion. Elimination involves the removal of false locations around the eye region while fusion involves merging the multiple quasi locations into the optimal location that is closest to the real one.

4.3.1 Eliminating false detection

Elimination only aims at the single Bayesian classifier. Note that, in so many output images of a single Bayesian classifier, incorrect detections (indicated by red rectangles in Fig. 5) often occur with less consistency. Because of this elicitation, an elimination strategy is devised to remove much false detection.

The elimination of false detection approach is outlined as follow:

A. Eye candidate windows are obtained in each single Bayesian classifier
B. The center of the eye candidate window is calculated, and each is spread out with some x, y, scale to form a rectangle
C. At each cluster of rectangles, the density of overlapping spread out rectangles is counted. The centroids of the rectangles in the cluster are collapsed into a single centroid.
D. The centroid with a density higher than the threshold is preserved.
E. Each surviving centroid has an expanded region. If there is overlapping between windows, the window with the lower density will be eliminated. The intersections of these remaining regions are saved as quasi eye windows. Size is defined by the average size of the participating candidate windows

4.3.2 Fusion of multiple detectors

To further improve accuracy, multiple Bayesian classifiers are applied. Each classifier is trained in a similar manner, but with different training conditions based on the first-level classifier. As a result, even though the detection results of every individual Bayesian classifier for the same image may be quite close, because of different training thresholds, the classifiers will have different biases and will make different errors. This will be used to fuse the output of each classifier in order to obtain higher accuracy.

In Fig. 5, an example shows the entire process flow from performing eye detection with multiple candidate Bayesian classifiers to deciding the final optimal eye position. In this figure, '1', 'i', 'j', and 'n' represent the serial numbers of clusters included in the AN. AN represents the set of all clusters. CN indicate the number of candidate clusters. In the proposed system, 1≤CN≤3, and CN=3 is used as an example. In Fig. 5, red squares present false eye detections and blue squares present modified eye regions using elimination of false detection approach.

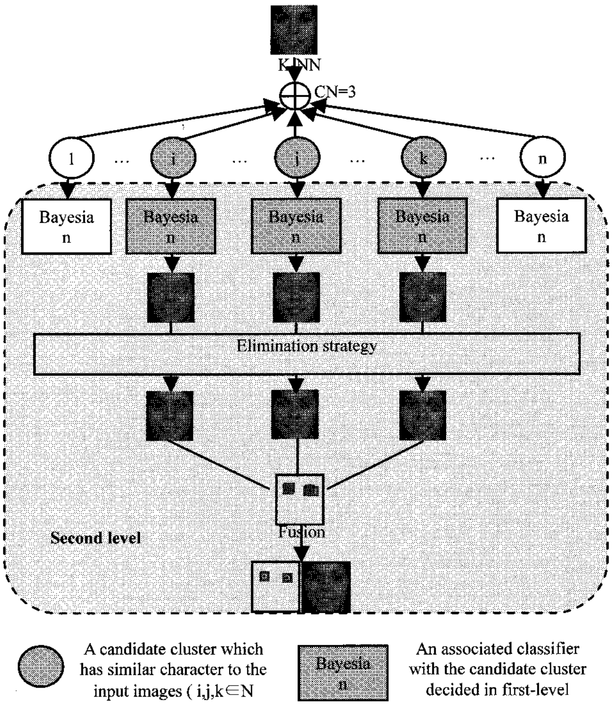

Fig. 5. An example of the process that decides the optimal eye location.

5. EXPERIMENTS AND RESULTS

In order to test the proposed scheme, several sets of experiments were performed. The data for the experiment was taken from the FERET database (3816 images) and BioID (1521 images), 5337 facial images in total. Based on previous research, there are many methods for evaluating the accuracy of eye location [14]. In this paper, a scale-independent localization measurement called relative accuracy of eye location is adopted to measure the accuracy of eye location [14]. This method aims to compare the manually marked eye location with the automatically detected eye location results from the proposed eye location system. C_L and C_R are defined as the manually assigned left and right eye centroids, $\tilde{C}_L$ and $\tilde{C}_R$ are the automatically detected left and right eye centroids. D_L is the Euclidean distance between C_L and $\tilde{C}_L$, D_R is the Euclidean distance between C_R and $\tilde{C}_R$. D is the Euclidean distance between the left and right eyes. The relative accuracy of detection is defined as follows [14]:

$$error = \frac{\max(D_L, D_R}{D}. \tag{8}$$

For each case, the evaluation criterion of (8) is a measure. In the proposed system, error values under 0.14 are regarded as acceptance-such a value indicates that the deviation values are smaller than 7 pixels on both databases. The performance of single Bayesian classifier using only the elimination strategy is shown in Table 1. From the table, it can be seen that the

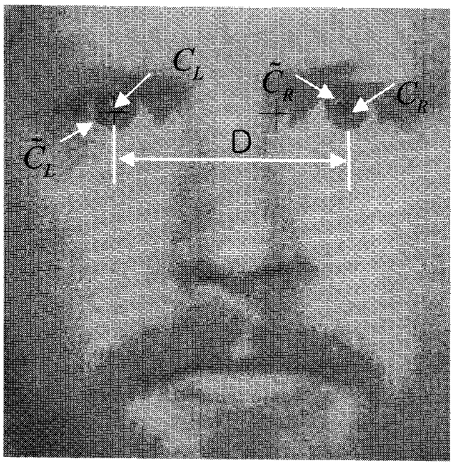

Fig. 6. An illustration of the centroids of the left and right eyes.

single Bayesian classifier performance is insufficient to meet the requirements of eye location.

Accuracy is paramount for an eye location system. As shown in Table 2, a set of experiments was undertaken to compare the performance of a non-level and the proposed two-level scheme for eye location systems. In total, 1093 images were randomly chosen from the database and the cluster number was varied range between 3 and 9, which was decided by k-means based on the illumination characters in the proposed system. The acceptance rate of the proposed scheme is obviously much better than for the non-level scheme. From the table it can be seen that although the average acceptance rate is highest when the training data is classified into nine clusters, not every cluster achieves better performance. Overall, based on the analysis of Table 2, it is concluded that the performance is best when the data context category is 3.

In order to further improve accuracy, multiple candidate clusters were employed instead of a single candidate cluster in the first level as the entrance into the second level. Owing to the complex environment, it is usually hard to identify the optimal candidate, i.e., when a test image is input, more than one cluster is identified as fitting the input image. Table 3 demonstrates the acceptancerate among different numbers of candidate clusters. From these results, it seems the optimal outcome can be obtained when three candidate clusters are employed.

Table 1. Performance of a single Bayesian classifier with elimination detection.

Source	Images	Accepted faces	False Detects	Acceptance rate
FERET	3816	3417	399	89.54%
BioID	1521	1392	129	91.52%
Total	5337	4809	528	90.11%

Table 2. Eye location comparison between the Non-level and Two-level classifiers.

Data context category	cluster	Images (total 1093)	Non-level method	Two-level classifier based eye location
Three-cluster	Cluster 1	289	94.12%	95.85%
	Cluster 2	677	96.75%	96.90%
	Cluster 3	127	93.70%	96.85%
	Average		95.70%	96.61%
Six-cluster	Cluster 1	213	92.01%	94.34%
	Cluster 2	87	94.25%	97.70%
	Cluster 3	567	95.77%	97.18%
	Cluster 4	40	92.50%	95.00%
	Cluster 5	19	94.74%	94.74%
	Cluster 6	167	97.00%	98.20%
	Average		94.97%	96.71%
Nine-cluster	Cluster 1	8	87.50%	87.50%
	Cluster 2	81	86.50%	91.40%
	Cluster 3	12	83.30%	91.67%
	Cluster 4	400	95.25%	97.50%
	Cluster 5	19	89.47%	89.47%
	Cluster 6	83	95.18%	97.59%
	Cluster 7	312	96.15%	98.40%
	Cluster 8	81	93.83%	96.30%
	Cluster 9	97	97.94%	98.97%
	Average		94.69%	97.07%

Table 3. Eye location performance comparison with different numbers of candidate clusters.

Source	Images	Classified into single candidate cluster	Classified into two candidate clusters	Classified into three candidate clusters
		Acceptance rate		
FERET	3816	89.54%	95.67%	97.56%
BioID	1521	91.52%	96.83%	97.29%

6. CONCLUSIONS

A two-level classifier scheme for an eye location system in Computer Vision has been presented in this paper. The objective of the first-level classifier is clustering step with identification involving training and testing. The goal of the second-level classifier is detection and location of the eye.

K-means was used for image clustering to account for various illumination levels and K-NN was used to identify the multiple candidate clusters that offer a fit to the input test image. It was observed that usually only one relative fit cluster is chosen for a test image.

As is well known, complex conditions always cause some confusion. It is not possible to simply pick the best candidate to fit the input. Therefore, having multiple candidate clusters is handy. These clusters are the output of the first level as well as the input of second level. In this second level, the associated multiple Bayesian classifiers work towards object detection. Moreover, an elimination strategy was used in each single candidate Bayesian classifier to remove the false detection and in order to further improve the accuracy. A fusion strategy was also used for combining the results after elimination.

An optimal eye location is obtained for a more accurate and efficient eye location system under varying environments by this process.

A set of experiments was presented to verify the strategy. The tables show the comparison of acceptance rates between using this proposed two-level scheme and using a non-level scheme for eye location in various illumination settings. The results provide evidence that when this scheme is incorporated in the proposed system, overall eye location performance is optimized. In addition, since the proposed scheme shows good performance, it is postulated that it can be used in the location of other tissues or in identification tasks for improved precision in various domains of application in biomedical imaging.

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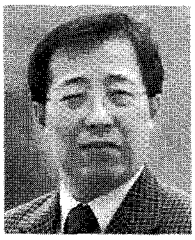

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