

An Algorithm to Detect Kayser-Fleischer Ring in Human Eye for Diagnosing Wilson Disease

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ABSTRACT-An eye image is segmented by JSEG (J measure based segmentation) algorithm without the manual parameter adjustment and simplifies texture and color for detecting the Kayser-Fleischer ring in diagnosing Wilson Disease. Segmentation with this algorithm passes through two major stages, namely color quantization and spatial segmentation as first stage and region growing and region merging as secondary stage. The biometric measurement provides information on the percentage of the extent of the cornea tissue affected from the copper accumulation. This algorithm detects the presence of symptoms reducing occurrence of false-negative diagnoses and improves accuracy of actual methods used in practice like slit lamp method. The described techniques reduces possible interpretation errors and assists doctor to diagnose the pathology.

INDEX TERMS – Wilson disease, Kayser-Fleischer Ring, segmentation, Biometric measurement.

I. INTRODUCTION

Wilson disease is an autosomal recessive genetic disorder that prevent the body from getting rid of extra copper. A small amount of copper obtained from food is needed to stay healthy, but too much copper is poisonous. When the copper storage capacity of the liver is surpassed, copper is passed into the bloodstream and travels to the other organs-including the brain, kidney, and eyes. In Wilson disease, excess copper builds up in the liver, brain, eyes and other organs [1][2]. The copper accumulation in eye leads to Kayser- Fleischer ring (KF ring) is shown in Figure 1, a pathognomonic sign visible in the cornea of the eyes and they are due to copper deposition in Descemet's membrane.



Sub1

Sub2

Sub3

Sub4

Figure 1. Kayser-Fleischer ring

Kayser -Fleisher rings result from a buildup of copper in the eyes and are the most unique sign of Wilson disease. They appear in each eye as a trusty-brown ring around the edge of the iris and in the rim of the cornea. The iris is the colored part of the eye neighboring to the pupil. The cornea is the transparent outer membrane that covers the eye. Without

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suitable therapy and treatments, symptoms tend to become progressively more and more acute and chronic, and the disease may be fatal. Unfortunately, diagnosis is made only when symptoms are apparent and critical, so treatment is typically late. But this represents the practical and evident symptom of the Wilson disease so different screening tool exist to diagnose this disease. Wilson

disease is diagnosed through a physical examination and laboratory tests [3]. During the physical examination, a doctor look for visible signs of Wilson disease. A special light called a slit lamp is used to look for Kayser-Fleischer rings in the eyes. Kayser-Fleischer are present in almost all people with Wilson disease who show sign of neurologic damage but are present in only 50 percent of those with sign of liver damage alone. Laboratory tests measure the amount of copper in the blood, Urine, and liver tissue. Most people with Wilson disease will have a lower than normal level of copper in the blood and a lower level of consistent ceruloplasmin. In case of acute liver failure caused by Wilson disease, the level of blood copper is often higher than the normal. A 24-hour urine collection will show increased copper in the urine in most patients who display symptoms. A liver biopsy- a process that removes a small piece of liver tissue, can show if the liver is recollecting too much copper. The examination of biopsied liver tissue with a microscope detects liver damage, which often shows a pattern unique to Wilson disease. Genetic testing may help diagnose Wilson disease in some people, particularly those with a family history of the disease. Wilson disease may be misdiagnosed because it is rare and its symptoms are similar to those of other conditions. Hence in medical prosecutions the presence of Kayser-Fleischer ring is considered critical for diagnosing the pathology. Therefore the detecting of this symptom represents an important and non-invasive diagnostic tool [4]. In fact ophthalmology studies show that almost all patients with neurological disorders have the Kayser-Fleischer ring but some false negative diagnoses are also possible. For these causes, an automated detection technique is used in order to evaluate the presence of kayser-Fleisher ring in patients with neurological or psychiatric disorders. Hence the suggested technique is innovative and is based on eye image processing by means of a segmentation algorithm [5]. Biometric measurements provide further information on the severity level of the disease. In fact the dimension of the ring is strictly correlated with the stage of pathology. The aim of the present research is to define an alternative and non-invasive screening method to reduced human interpretation errors.

In section II more details on Wilson disease and the associated symptoms are reported. Neurological disorders and the Kayser-Fleischer are described [6]. The section III reports the suggested algorithm for detecting Kayser-Fleischer ring and the biometric parameters are described [7]. The section IV provides experimental results and biometric measurements. The section V describes final conclusion on the findings and perspectives for future work

II. METHODS AND APPROACHES

In medical application image processing technique is used to detect specific anatomical structures or regions. Therefore through image segmentation process here the Kayser-Fleischer ring had been detected, segmented and analyzed through a JSEG algorithm [12][13]. The essential idea of JSEG is to separate the segmentation process into two independently processed stages, color quantization and spatial segmentation. In the first stage, colors in the image are quantized to several representing classes that can be used to separate regions in the image. This quantization is achieved in the color space alone without considering the spatial distributions. Subsequently, image pixel colors are replaced by their corresponding color class labels, thus forming a class-map of the image. The main focus of this work is on spatial segmentation, where a criterion for "good" segmentation using the class-map is proposed [14]. Applying the criterion to local windows in the class-map results in the "J-image", in which high and low values correspond to possible boundaries and interiors of color-texture regions. A region growing method is then used to segment the image based on the multi-scale J-images and finally they merged to obtain the segmented image. The benefit of this separation is that individually evaluating the similarity of the colors and their distribution is more tractable than complete them at the same time [19]. Figure 2 shows the procedure of flow-chart. It summarizes the main steps of the segmentation process previously described.

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Initial step is the color quantization, where the input image is color quantized to several representing classes to discriminate regions in the image. Quantization is performed in color space without considering the spatial distributions. During color quantization the image quality is not degraded that considerably [16]. Standard 256 color palette is consider in order to extract set of representation color to single out neighbor region of pixels. Therefore based on 256 palette color set is formed. For a color image each pixels in an image contains RGB image in it. Hence from RGB values each pixels have their matching class.

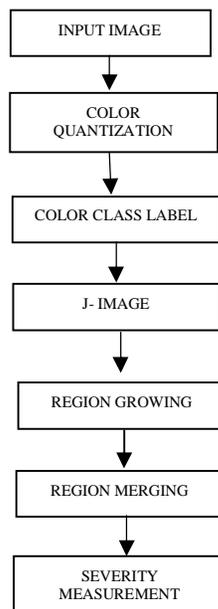


Figure 2 Flow chart of JSEG algorithm

Finally these matched class are assigned label called image class where they are assigned as class map. Hence the color quantization had been done but for good segmentation result we are undertaking spatial segmentation. Considering a 2-D plane xy , the class-map can be modeled as spatial data points located in the plane. so the bi-dimensional function $L(x,y)$ provides the label of the pixel with position (x,y) . This is the value of the class-map at that position of the image. The second step of the algorithm performs a spatial segmentation starting from the class-map. Suppose that the image has been classified into N_c classes. Let CM be the new class-map image. Whereas CM_i represents the set of all pixels contained in the i -th class, with $i=1, \dots, N_c$. Assume m to be the spatial mean of all data points $z=(x,y)$ in CM :

$$m = \frac{1}{N_{dp}} \sum_{z \in CM} Z(1)$$

Where N_{dp} is the number of data points or pixels belonging to CM . let m_i be the spatial mean of the $N_{dp,i}$ data points of the class CM_i :

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$$m_i = \frac{1}{N_{dp,i}} \sum_{z \in CM_i} Z \quad (2)$$

Assume V_t to be the total variance of all data points in CM:

$$V_t = \sum_{z \in CM} \|Z - m\|^2 \quad (3)$$

Whereas $V_{t,CM}$ is the total variance of the pixels in CM belonging to the same class CM_i ;

$$V_{t,CM} = \sum_{i=1}^{N_c} \sum_{z \in CM} \|Z - m\|^2 \quad (4)$$

The degree of the distribution of the colour classes J can be obtained by the following expression:

$$J = \frac{V_t - V_{t,CM}}{V_{t,CM}} \quad (5)$$

The distribution degree provide useful information about the distribution of the classes in the class-map. This parameter is used to optimize the segmentation process. In order to complete the spatial segmentation, the average J_m and local J_k distribution values have to be estimated. The average J_m distribution value provides information about the performance of segmentation. If the class-map is divided in K regions, the average J_m value is obtained as sum over all the regions of the local J_k values estimated in the K -th region:

$$J = \frac{1}{N_{dp}} \sum_K N_k \cdot J_k \quad (6)$$

Where N_k is the number of pixels in the K -th region. Low J_m values indicate good segmentation results. This happens when each region has few uniformly distributed labels. The algorithm executed recursively so to optimize progressively the segmentation. Once the J -image is obtained, the algorithm minimizes the average J_m value by considering the local area of the class-map. To this aim, different windows centred at the single pixel are iteratively considered in order to estimate the local homogeneity. In this way a J -image is generated as a gray-scale image, whose pixel values are the J_k values calculated over the local window centred on each pixel. So high local J_k value show pixel more near to a boundary or to a region. The size of the local window shown in Table I determines the size of the region to be detected. Therefore small windows allow intensity or colour edges to be detected. While, large windows allow texture boundaries to be detected. Different scales are used for image segmentation. The smallest scale used is a 9×9 without considering the corners. A region- growing method has been used to complete the segmentation process. The spatial segmentation starts to segment the region with an initial large scale until the fixed minimum scale.

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Scale	Window (Pixels)	Sampling (1 / Pixels)	Region Size (Pixels)	Min. Seed (Pixels)
1	9×9	1 / (1×1)	64×64	32
2	17×17	1 / (2×2)	128×128	128
3	33×33	1 / (4×4)	256×256	512
4	65×65	1 / (8×8)	512×512	2048

Table I Window size at different scales.

Initially whole image is consider as a single region. The region-growing algorithm is repeated on the newly segmented regions at the next lower scale. When the segmentation at the fixed minimum scale is completed, the final segmentation is got by merging according to the fixed similarity criterion. The initial seed area of the segmentation is determined as the area with the lowest J value. The new regions of the segmented image grow from the seed area by means of the region-growing algorithm. Regions are subsequently merged based on the similarity of their labels. The used similarity criterion is the Euclidean colour distance between the labels of two regions. Considering there RGB colour system, let be $l_1 = (R_1, G_1, B_1)$ the label of the first region and $l_2 = (R_2, G_2, B_2)$ the label of the second region.

The Euclidean colour distance can be estimated by the following expression:

$$\Delta D = \sqrt{(R_1 - R_2)^2 + (G_1 - G_2)^2 + (B_1 - B_2)^2} \tag{7}$$

Adjacent regions are merged if this distance is lower than a fixed threshold level ΔD_{ref} . This threshold level is equal to the standard deviation of the labels of the K neighbouring region. In details when the region merging is finished, the segmentation process is completed.

B. The Biometric measurement

In order to estimate the severity of the pathology, an innovative biometric measurement has been defined. In detail, in the next step, the algorithm measures the extent of the Kayser– Fleischer ring by counting the number of pixels of the eye image affected from the oxidative process. Let $N_{KF,r}$ be the number of pixels associate with the Kayser–Fleischer ring. In order to estimate the percentage of the oxidized eye area, the region of the iris is considered. Let N_e be the number of pixels of iris region. In this way, it is possible to estimate the extent of the Kayser–Fleischer ring by the equation:

$$\%p = \frac{N_{KF,r}}{N_e} \tag{8}$$

This measurement provides information on the percentage of the extent of the corneal tissue affected from the copper accumulation. The copper has an oxidative effect on the tissue and it causes golden brown pigmentation in the iris. Hence this pigmentation formation is the unique sign of the Wilson disease of an individual with neurological disorder. The extension of this oxidative process shows the quantity of copper observed by the eye cornea. Thus by measuring the extension of oxidative process in the iris severity level can be identified and immediate treatment can be done, since the appearance of K-F ring is considered as the critical stage of Wilson disease.

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IV. EXPERIMENTAL RESULT AND BIOMETRIC MEASUREMENTS

The acquiring eye image consisting of K-F ring. It is a golden-brown, sometimes orange or greyish, ring because of copper deposit in the cornea is the input eye image shown in Figure 3.



Sub1 Sub2 Sub3 Sub4

Figure 3 Input eye image of K-F ring

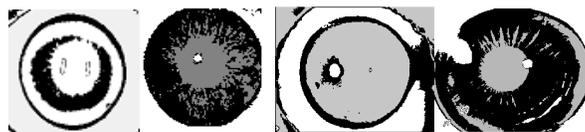
After this initialization, the clusters are adapted using classic K-Means algorithm. This quantization method quantizes the set of image pixels to the same color, called color class. Then the image pixel colors are replaced by their corresponding color class label and the newly established image of labels is the color quantized output is shown in the Figure 4.



Sub1 Sub2 Sub3 Sub4

Figure 4 Color quantization of the input image

Through the thresholding technique J-image is generated as a gray-scale image shown in Figure 5 whose pixel values are the J_k values calculated over the local windows centred on each pixel.



Sub1 Sub2 Sub3 Sub4

Figure 5 Spatial segmentation j- image formation

According to the characteristics of the J values, the region growing method is applied to segment an image. The algorithm starts the segmentation at the largest scale. Then it repeats the same process on the newly segmented regions at the next lower scale. And finally the affected region is segmented shown in Figure 6.

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Sub1 Sub2 Sub3 Sub4

Figure 6 Region growing of K-F ring

In order to identify the percentage of severity in the cornea, iris should be segmented. Therefore this iris segmentation helps for the accurate percentage measurement of the copper deposition in the cornea. Figure 7 shows the iris segmentation of the input image.



Sub1 Sub2 Sub3 Sub4

Figure 7 Iris segmentation

Thus the biometric parameter provides information on the percentage of the extent of the corneal tissue affected from the copper accumulation ratio of Kayser–Fleischer ring in iris (%) = 36.696 is shown in Figure 8.



Sub1 Sub2 Sub3 Sub4

Figure 8 Severity of Kayser-Fleisher Ring

Input mage	Ratio of Kayser–Fleischer ring in iris (%)
Sub 1	36.696
Sub 2	87.8405
Sub 3	89.3723
Sub 4	96.0944

Table II. biometric measurements for input images

This above Table II shows the biometric measurements for the various input images used. The value represents the amount of copper accumulation in the eye and the severity of the Wilson disease.

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V. CONCLUSION

In this paper, the JSEG algorithm, detects the occurrence of Kayser–Fleischer ring in the eye due to Wilson disease. Through biometric measurement further information on the area extent of the iris affected from the Kayser–Fleischer ring is obtained and thus improved the knowledge on the stage and seriousness of the pathology. Thus the present work had provided a non-invasive screening tool for physicians, reducing occurrences of false negative diagnoses. The biometric measurements is able to allow physician to get further information on the deteriorative effects of the copper accumulation in the cornea. Thickness, extension, shape and position of the Kayser–Fleischer ring can optimize the choice of the most appropriate therapy.

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