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Simplified Fuzzy Approach for Cataract Identification

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Abstract

The prevalence of cataract across Nigeria, Africa and the rest of the world is indeed alarming. Objective diagnosis and identification is crucial to patient treatment. This research paper proposes an objective approach for cataract diagnosis with the rich providence of fuzzy logic. This research paper propose a fuzzy rule approach for diagnosing cataract utilizing the decision variables pertaining to cataract, thereby enhancing or extending the traditional (conventional) method. The result obtained based on the fuzzy scale was subdivided into three: "Cataract Absent", "Moderate Cataract "and Cataract Diagnosed". The proposed expert system eliminates uncertainties and imprecision associated with the cataract Diagnosis.

Keywords: Diagnosis, Cataract, Fuzzy Classifier, Fuzzy set, Fuzzy Logic, Recognition,

1.0 Introduction

A cataract is an eye disease in which the clear lens of the eye becomes cloudy or opaque, causing a decrease in vision (Healthline, 2014, MedicineNet, 2014 and RightDiagnosis, 2014).

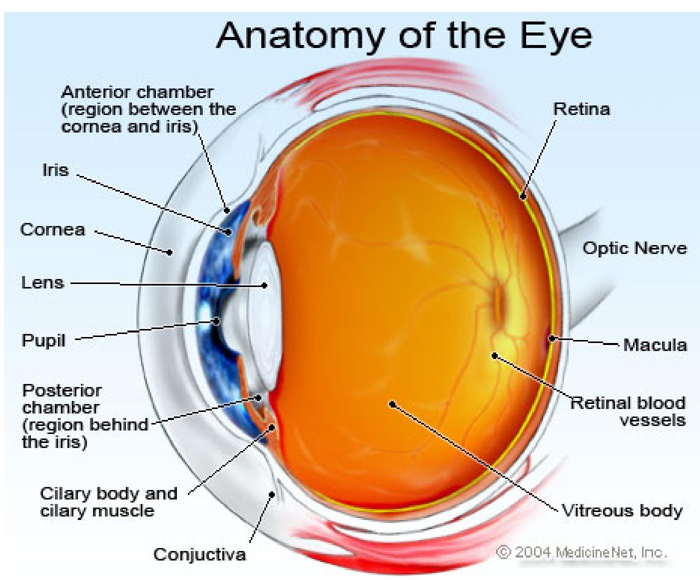

Figure 1: The Anatomy of the Eye (MedicineNet, 2014)

The lens is a portion of the eye that normally clears (Healthline, 2014). It focuses rays of light entering the eye onto the retina, the light-sensitive tissue at the back of the eye. In order to get a clear image onto the

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retina, the portions of the eye in front of the retina, including the lens, must be clear and transparent. The light initiates a chemical reaction within the retina (Wrong Diagnosis, 2014). The chemical reaction, in turn, initiates an electrical response which is carried to the brain through the optic nerve. The brain then interprets what the eye sees (MedicineNet, 2014).

In a normal eye, light passes through the transparent lens to the retina. The lens must be clear for the retina to receive a sharp image. If the lens is cloudy from a cataract, the image striking the retina will be blurred and the vision will be blurred. The extent of the visual disturbance is dependent upon the degree of cloudiness of the lens.

Most cataracts are related to aging. Cataracts are very common in older people (MedicineNet, 2014).By age 80, more than half of all Americans either have some degree of cataract or have already undergone cataract surgery in one or both eyes. By age 95, this percentage increases to almost 100% (Healthline, 2014 and MedicineNet, 2014 and RightDiagnosis, 2014). A cataract can occur in either or both eyes. Individuals with a cataract in one eye usually go on to develop a cataract in the other eye as well. A cataract is not contagious and cannot spread from one eye to the other or from person to person (Mycoclinic, 2014). Cataracts do not cause the eye to tear abnormally. They are neither painful nor make the eye itchy or red (Healthline, 2014).

The causes of cataract includes: changes to the protein of the lens, also resulting in visual blurring or visual loss. Blunt or penetrating injury to the eye may cause, Eye surgery for other conditions can also cause cataracts, excessive exposure to ionizing radiation (X-ray), infrared radiation (as in glass blowers) and ultraviolet radiation (Mycoclinic, 2014 and Healthline, 2014). Diabetes is associated with the development of secondary cataracts. Inflammatory disease of the eye, such as iritis or uveitis, may cause or accelerate the development of cataract in the involved eye There are many genetic illnesses that are associated with the development of secondary cataracts. These include myotonic dystrophy, galactosemia, homocystinuria, Wilson's disease and Down syndrome, plus many others. Congenital infections with herpes simplex, rubella, toxoplasmosis, syphilis, and cytomegalic inclusion disease may also result in cataracts.There are many medications which, when taken over a long period of time, can cause secondary cataracts. The most common of these are oral corticosteroids, such as prednisone, which are used for a wide variety of medical conditions (Healthline, 2014 and RightDiagnosis, 2014.

The symptoms of cataract include; clouded, blurred or dim vision, increasing difficulty with vision at night, sensitivity to light and glare, seeing "halos" around lights, frequent changes in eyeglass or contact lens prescription, Fading or yellowing of colours, double vision in a single eye.

This research paper propose a Fuzzy- Rule Approach for Cataract Identification (FRACI)

2.0 Review of Related Literature

A **Fuzzy *classifier*** is an algorithm that assigns a class label to an object, based on the object description. It is also said that the classifier *predicts* the class label (Angelov and Zhou, 2008). The object description comes in the form of a vector containing values of the features (attributes) deemed to be relevant for the classification task (Ishibuchi et al., 1995, Takagi and Sugeno, 1985, Yager and Kacprzyk, 1997). Typically, the classifier learns to predict class labels using a training algorithm and a training data set. When a training data set is not available, a classifier can be designed from prior knowledge and expertise. Once trained, the classifier is ready for operation on unseen objects (Cordon et al., 1999, Roubos et al., 2005).

Classification belongs to the general area of pattern recognition and machine learning (Babuska, 1998) which includes:

a. *Soft labelling.* The standard assumption in pattern recognition is that the classes are mutually exclusive. A standard classifier will assign a single *crisp* label. A fuzzy classifier can assign degrees of membership (*soft* labels). A fuzzy classifier, D ,producing soft labels can be perceived as a function approximator D:F→[0,1]c, where F is the feature space where the object descriptions live, and c is the number of classes. While tuning such a function approximator outside the classification scenario would be very difficult, fuzzy classifiers may provide a solution that is both intuitive and useful (Mamdani 1977, Nauck et al., 1997 and Kuncheva, 2000).
b. *Interpretability.* Automatic classification in most challenging applications such as medical diagnosis has been sidelined due to ethical, political or legal reasons, and mostly due to the *black box* philosophy underpinning classical pattern recognition. Fuzzy classifiers are often designed to be *transparent*, i.e., steps and logic statements leading to the class prediction are traceable and comprehensible (Kuncheva, 2003).
c. *Limited available data and expert expertise.* Examples include predicting and classification of rare diseases, oil depositions, terrorist activities, natural disasters. Fuzzy classifiers can be built using expert opinion, data or both.

The simplest fuzzy rule-based classifier is a fuzzy if-then system, similar to that used in fuzzy control which is clearly exemplified below

IF X1 is medium and X2 is small Then Class is 1
IF X1 is Medium and X2 is large Then Class is 2
IF X1 is large and X2 is small Then Class is 2
IF X1 is Large and X2 is small Then class is 3
If X1 is small and X2 is large Then Class is 3

The two features $x1$ and $x2$ are numerical but the rules use *linguistic values*. If there are M possible linguistic values for each feature, and n features in the problem, the number of possible different if-then rules of this conjunction type (AND) is Mn. If the fuzzy classifier comprises of all such rules, then it turns into a simple look-up table. Unlike look-up tables, however, fuzzy classifiers can provide outputs for combinations of linguistic values that are not included as one of the rules. Each linguistic value is represented by a membership function.

3.0 Methodology

The methodology is geared toward specifying fuzzy rules utilizing fuzzy set theory application, linguistics variable and appropriate membership function. We utilize several symptoms (Linguistic variables) of cataract(clouded vision, increasing difficulty with vision at night, sensitivity to light and glare, seeing "halos" around lights, frequent changes in eyeglass or contact lens prescription, Fading or yellowing of colours, double vision in a single eye) and several linguistic values (High, Moderate, Minor and Low). Each of these symptoms fall into rule (R1, R2… R6). The fuzzy rules Specifies

a. IF a patient exhibit $S \leq 2$ THEN Cataract Absent
b. IF a patient exhibits $S = 3$ THEN ModerateCataract
c. If a Patient exhibits $S \geq 4$ THEN Cataract Diagnosed.

Therefore the fuzzy set rules are thus:

R1: If Cloud vision is ***Low***THEN CATARACT ABSENT

R2: If Cloud vision is***Low,*** difficulty with Night Vision is***Minor*** THEN CATARACT ABSENT

R3: If Cloud vision is ***Moderate,*** difficulty with Night Vision is***Moderate***and seeing Hale is ***Moderate*** THEN MODEST CATARACT

R4: If Cloud vision is***High,*** difficulty with Night Vision is***High,*** seeing Hale is ***High*** and Frequent Glass change is ***High***THENCATARACT DIAGNOSED

R5: If Cloud vision is***High,*** difficulty with Night Vision is***High,*** seeing Hale is ***High,*** Frequent Glass change is ***High*** and Fading of colours is ***High***THEN CATARACT DIAGNOSED

R6: If Cloud vision is***High,*** difficulty with Night Vision is***High,*** seeing Hale is ***High,*** Frequent Glass change is ***High*** , Fading of colours is ***High*** and Double sing eye vision is ***high***THEN CATARACT DIAGNOSED

4.0 Discussion

The main focus of our approach is geared toward designing a Fuzzy Rule approach for the diagnosing of Cataract disease utilizing the rich facilities of fuzzy logic which is more objective and robust in fusing certain linguistic values to certain linguistic variables. Previous approach obtain recognition solely on symptoms recognition neglecting, the linguistic value, which invariably tied the level of occurrence. Previous approaches are also times consuming and quite expensive because of repeated unnecessary test, the current approach propagated is a simple fuzzy based approach in handling imprecision.

5.0 Conclusion

An objective approach has been attuned utilizing the fuzzy linguistic variables, linguistic values for and fuzzy rule for cataract diagnosis.

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