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Development of a Mobile Phone Based Ophthalmoscope for Telemedicine

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Abstract - **Regular retinal examinations can contribute to the management of both hypertensive and diabetic retinopathy. One of the most successful means of evaluating these retinopathies is by means of a fundus camera generating a fundus photograph. Patients in rural clinics unfortunately often lack the financial means to undergo regular examinations. This study produced a handheld ophthalmoscope that combines with a digital camera to capture retinal images. The images are transferred to a mobile phone and then sent to a central website for evaluation. The evaluation report is automatically returned to the mobile phone via SMS. The quality of the images was rated as acceptable for clinical use by medical specialists at the Department of Ophthalmology of the Health Sciences Faculty of Stellenbosch University, South Africa.**

I. INTRODUCTION

The South African public health care system is overburdened and under resourced with only 26 public service medical practitioners per 100 000 of the population. The distribution of medical practitioners in the South African public service, as shown in Table 1, is such that great reliance is placed on nurses in rural clinics, especially in the Eastern Cape, Limpopo and Mpumalanga [1] .

Table 1: 2008 Public service medical practitioners per 100 000 population [1]

EC	FS	GP	KZN	LP	MP	NC	NW	WC
17 9	23 2	32 0	34 7	17 4	18 3	35 7	14 1	37 9

EC: Eastern Cape FS: Free State GP: Gauteng
KZN: KwaZulu-Natal LP: Limpopo MP: Mpumalanga
NC: Northern Cape NW: North West WC: Western Cape

According the 2008 South African Health Review, nurses working in clinics often lack the skills to deal comprehensively with chronic diseases [2]. It is also stated that chronic disease conditions and risk factors are infrequently diagnosed and inadequately treated, resulting in high levels of uncontrolled hypertension and diabetes. These two conditions are ranked second and eighth of those risk factors listed as the underlying cause of death in South Africa.

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The South African Department of Health's directorate of chronic diseases, disabilities and geriatrics states that diabetic retinopathy accounts for 8% of blindness and recommend that diabetic patients should have a fundal examination once a year [3]. Hypertensive retinopathy can also be identified by fundal examination before any vision loss is noticed by the patient. Regular fundoscopy can therefore contribute to the management of both hypertension and diabetes. With this application we propose the development of a mobile phone-based fundoscope system to facilitate regular fundal exams for the rural areas of Southern Africa.

A research report by the American Academy of Ophthalmology concluded that there is evidence that single-field fundus photography can serve as a screening tool for diabetic retinopathy (DR) [4]. A single-field fundocsope that delivers images via GPRS to one of the major centres can therefore contribute significantly to the improved management of two of the important chronic conditions listed as inadequately treated in rural areas of Africa.

II. PREVIOUS RESARCH

Studies have been performed to find the reliability of non-mydriatic cameras in the screening of DR specifically in rural populations [5]. Such studies have shown that the screenings improved the quality of the ocular follow-up in diabetes patients within the control groups. In comparison, some authors have studied the benefits of telemedical networks such as the Ophdiat® system on the screening for DR; they found that such systems improved the mean time per diagnosis of DR [6]. In contrast others suggested the development of a computer-aided system to help scan retinal fundus images to detect the presence of microaneurysms [7]. Osareh *et al*. extracted features such as color, edge strength, size and texture, from which fuzzy c-means clustering was used to normalise the features and help determine best classification results by means of neural networks [8]. Yagmur *et al.* also performed numerous studies into the recognition of different types of retinal disorders with use of neural networks, including that of DR, Hypertensive retinopathy, Macular Degeneration, Vein Branch Oclusion, Vitreus hemorrhage and their differences to normal retina [9].

Methods of analysing retinal images include looking at the following features: exudates, bifurcation angle, artery-to-vein diameter rations, mean diameters, form and size of optic discs and vessel tortuosity

[10]; with the evaluation of these features it was seen that different feature deviations indicated different disorders, proving that automatically generated retinal images features is an effective screening method for the detection of diabetes and hypertension [11]. The need for improved equipment and diagnostic tools can be seen in the steady increase of cases of Retinopathy of Prematurity (ROP) blindness in premature babies due to the effects of supplemental oxygen [12]. In 2008 it was estimated that at least 50,000 children are blind from ROP which is becoming a significant cause of blindness in middle and low income countries due to the lack of proper healthcare and equipment [13]. Lad *et al*. proposed the development of a series of baseline characteristics, demographic information, and surgical interventions based on the USA national database of newborn infants and the incidence of ROP for use in diagnosing different forms of ROP early on in paediatric development [14].

III. OPHTHALMOSCOPE SYSTEM

Fixed line communication is not available in many rural areas of South Africa due to lack of investment, poor management and inadequate private sector involvement [15]. However, mobile phone network coverage is extensive and is thus employed in this study. An additional advantage is that the computational power of a suitable mobile phone eliminates the requirement for a computer in the clinic.

For the purposes of developing a prototype system to test the feasibility of the concept, a bracket was designed that allows a digital camera to be mounted on a standard Welch Allyn Panoptic Ophthalmo-scope. Figure 1 shows the first prototype of the attachment together with the digital camera and the Panoptic ophthalmoscope.

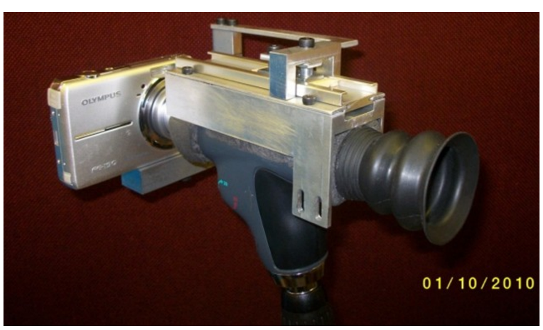

Figure 1: Prototype of mobile Ophthalmoscope

An Eye-Fi Pro X2 Wi-Fi interface card inserted into the memory card slot of the camera enables ad-hoc wireless communication between the camera and the mobile phone. Using this interface, images are transferred automatically to the phone.

Custom software was developed that can be uploaded on a Smartphone. As the software on the mobile phone requires a reasonable amount of computing power to perform image verification, a Smartphone with Windows Mobile operating system was employed. The software on the phone allows a nurse to enter the patient's information, such as name, age, sex, etc. The image verification algorithm automatically evaluates the retina images that are uploaded. This gives feedback to the nurse directly after capturing the images. The image verification algorithm checks the images for blur, color, resolution, outline border and whether the optical disc is within the image. The algorithm acts as an aid to the nurse, ultimately allowing him/her to decide whether the images are acceptable to upload on the web platform, or whether further images must be taken.

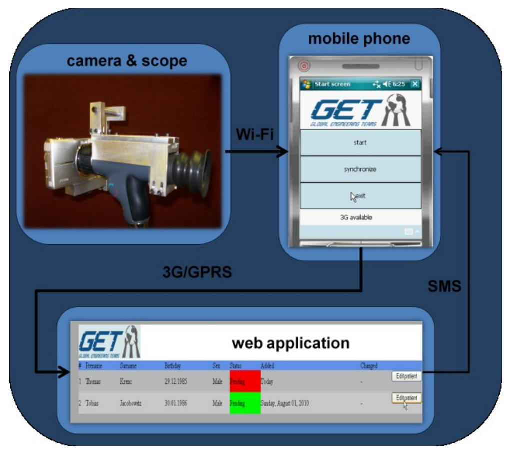

Figure 2: Information flow through system

After the patient's information is added to the retinal images, it is sent via 3G or GPRS (whichever is most readily available) to the central website. An Ophthalmologist can sign into the web platform, evaluate the images and perform a diagnosis. When the evaluation is complete, the nurse automatically receives an SMS on the Smartphone and can review the outcome of the specialist's diagnosis and treatment prescription. Figure 2 shows the flow of the system with the opening pages of both the mobile phone user interface and the central website.

IV. IMAGE ANALYSIS

While checking the image of the retina for black borders, proper resolution, file size and brightness is a rather trivial task, some analysis is required before implementing the blur check or locating of the yellow spot (optical disc).

Brightness, for instance, can be easily read out of all pixels and summed. Based on the sum, the algorithm can decide whether or not the image has a reasonable brightness. Blur, on the other hand, cannot be determined directly. As the bandwidth is reduced when an image is blurred, a two-dimensional Fast Fourier Transform (FFT) can be used to quantify blurring. The solution in this case was to let the FFT run on a set of good retina images to establish an empirical norm for the camera employed in the prototype

In order to find the yellow spot, the green value of every pixel of the image is read into a buffer to analyze the distribution of green values. Experimental analysis yielded that 55 is the most common green value in the retina image (between 0 - 255). Since the algorithm is supposed to find the yellow spot, bright green values are most relevant. But since images of retinas may differ in terms of the size of the yellow spot and the proportions of the retina, the bright green values have to be searched for in every image individually.

The algorithm traverses the image pixel by pixel and assigns a single, ideally unique, value (hash) with locality awareness to each pixel. Consequently similar hash values refer to the same region in the Euclidean space of the image. The algorithm calculates the hash value for every x-y pair by multiplying their distance to the origin and the angle to the x-axis. Although the color value of each pixel is known, only the blue value is left to be used for the hash value (red cannot be used, since the red values vary little across the retina and green was already used to filter the pixels). This lead to the following equation:

$$H = \text{distance} \times \text{angle} \times \text{blueValue} \qquad (1)$$

This equation provides good hash values for each x-y pair and the algorithm can now define several candidates for the yellow spot. As the yellow spot is usually surrounded by a substantial number of blood vessels, the algorithm has to check each candidate for a certain ratio of blood vessels in its region. The algorithm utilizes this principle to locate the yellow spot on a retina image.

V. RESULTS

Figure 3 shows example images captured with the mobile ophthalmoscope on the right, compared to images captured with a commercial system on the left. Note that although the commercial system yields better quality images, the commercial system is orders of magnitude more expensive and is bound to a laboratory. In order to test the efficiency of the image verification algorithm, several images were evaluated. Firstly, 30 images from a commercial system were evaluated and the algorithm indicated that all the images were acceptable. Next, images taken with the prototype ophthalmoscope were analyzed. Figure 4 shows two example images that were indicated to be acceptable (the algorithm covers the optic disc and displays this as the black and white pixels on the image).

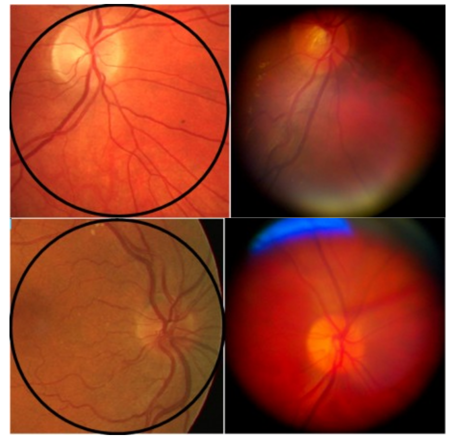

Figure 3: Images taken with a commercial system (left), in comparison with images taken with the prototype opthalmoscope (right)

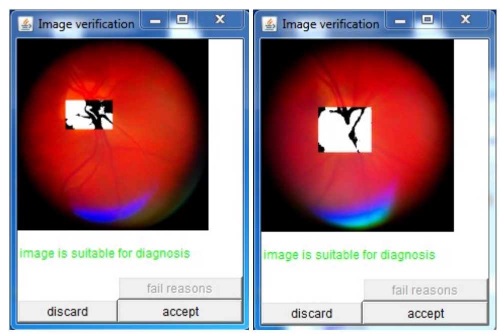

Figure 4: Acceptable images

Figure 5 shows two example images from mobile ophthalmoscope that were indicated to be unacceptable by the algorithm (note that feedback to the user is given directly below the image).

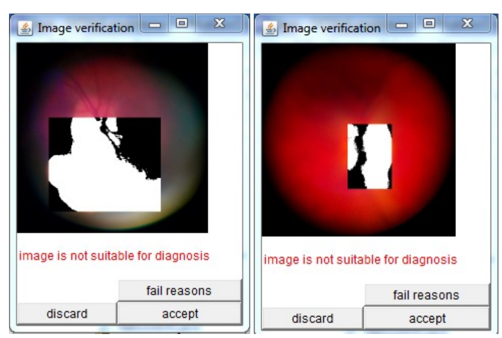

Figure 5: Unaccetable images

Barting *et al.* [16] concluded that automatic quality evaluation of fundus photographs based on illumination and sharpness were more sensitive than human observers. However, to confirm the clinical acceptability of the images deemed acceptable by the algorithm, the images were also evaluated by an ophthalmologist at the Department of Ophthalmology of Stellenbosch University, Faculty of Health Sciences. He confirmed that the images were acceptable for clinical use.

VI. DISCUSSION

There are some limitations associated with the prototype system. The first is the fact that the ophthalmoscope is only capable of capturing a 25° viewing area, whereas commercial systems are capable of capturing a 45° area. Secondly, an inadequate number of images were available to optimize the image verification algorithm. Upon considering future developments, the first step would be to enable a larger field of view from the ophthalmoscope. This could be achieved by combining multiple images or video frames to form one large image.

Diabetes affects 5%-10% of the adult population in South Africa [16]. A recent pilot project in the Cape Flats to screen for diabetic retinopathy made use of a Canon digital non-mydriatic EOS 2OD fundus camera. The camera costs approximately $25 000 is not easily transportable. In that study, the rate of diabetic screening at the participating clinics rose from 18% to 42% [17]. The project concluded that four mobile screening systems would be required to ensure annual screening of all diabetic patients in the Cape Town area, however the district health services do not have adequate funds to finance such systems.

VII. CONCLUSION

The low cost of the system proposed in this paper would enable the Cape Town district health services to equip 12 healthcare centres at the same cost as for one EOS 2OD fundus camera. Furthermore, the mobility of the system enables it to be used in rural areas as a telemedicine tool. The mobile ophthalmoscope can capture digital images and send these together with patient information to a website for evaluation by an ophthalmologist. The work could be expanded further to include routine retinal screening in low income communities around Cape Town, as well as rural areas in South Africa.

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