Design of a Mobile Face Recognition System for Visually Impaired Persons

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Abstract—It is estimated that 285 million people globally are visually impaired. A majority of these people live in developing countries and are among the elderly population. One of the most difficult tasks faced by visually impaired persons is identification of people. While naturally, voice recognition is a common method of identification, it is an intuitive and difficult process. The rise of computation capability of mobile devices gives motivation to develop applications that can assist visually impaired persons. With the availability of mobile devices, these people can be assisted through an additional method of identification through intelligent software based on computer vision techniques. In this paper, we present the design and implementation of a face recognition system for the visually impaired through the use of mobile computing. We propose a mobile based face recognition system with cloud support for assisting visually impaired persons. The system was tested on a custom video database. Experiment results show high face detection accuracy and promising face recognition accuracy in suitable conditions. The challenges of the system lie in better recognition techniques for difficult situations in terms of lighting and weather.

I. INTRODUCTION

It is estimated that 285 million people globally are visually impaired with 39 million blind and 246 million with low vision [1]. Approximately 90% of these people live in developing countries and 82% of blind people are aged 50 and above. Visually impaired persons adapt to life by using various assistive methods such as the white cane, sensory substitution and electronic devices [2], [3]. The white cane is a common mobility tool used by visually impaired people [4]. Sensory substitution is accomplished by using another sense to compensate for the lack of another. Research has shown that individuals which are blind from an early age have enhanced hearing compared to those with late blindness and sighted individuals [3], [5].

Electronic assistive systems use sensors or other methods to aid visually impaired users [6], [7]. They normally concentrate on providing navigation in indoor, outdoor or both environments [8], [9]. Navigation is commonly provided through the use of systems which employ some form of computer vision to detect obstacles, paths and perform location determination. These systems often utilize Global Positioning System (GPS) devices and web-based location services when providing navigation in outdoor environments due to their high accuracy [8]. For indoor navigation, various types of Radio-Frequency Identification (RFID) based systems have been used to assist users in navigation by supplementing computer vision systems [9], [10], [11]. Most RFID based systems use passive tags which are inexpensive and do not require a power source when not in use [12].

While there are several systems for assisting visually impaired persons in navigation, there are relatively few systems which help them locate and identify specific objects [13], [14], [6]. Object detection and recognition are among the most difficult tasks faced by visually impaired persons. Object detection is the process of locating objects in a given environment [15].

An object detection system was proposed by authors in [16] where a barcode based system for assisting users in identifying objects at museums and shopping centres. The system used a mobile phone camera to scan Quick Response (QR) codes attached to an object. Once the barcode was decoded, the phone’s browser would retrieve an audio file containing a description of the object from the internet and playback its content to inform the user.

Another object detection system supported users by detecting the presence of doors [17]. The system consisted of a camera and a computer. Features such as edges and corners were utilized to detect doors and distinguish them from other similar objects. In addition, the proposed method was found to be robust against variations in color, texture, obstructions, illumination, scale and viewpoints. Experiments done by the authors showed the algorithm achieved an accuracy of 91.9% with a false positive detection rate of 2.9%.

Object recognition takes the process of object detection further by identifying the detected object [15], [18]. To accomplish this, object recognition systems are trained on a training dataset that determines which objects will be recognised. This allows object recognition systems to be used in a variety of applications such as counting, sorting and scene categorization [19]. While this is a strength of object recognition systems, it can also be a weakness since recognition becomes limited to a specific class of objects. Attempting to solve this problem by including more classes in the training dataset increases training time and can also affect the performance. Variances in lighting, rotation, shape and size of objects are also some of the challenges faced by object recognition systems [20].

An object recognition system was developed by researchers in [21]. The system was an improvement on a previous object recognition approach by the same authors [22]. To achieve improvements over the previous approach, the authors used local and global descriptors to represent images, performed...
dimensionality reduction of the texture descriptors using PCA-SIFT [23] and using a bag-of-words (BoW) approach to compute textons among other methods. According to the authors, textons refer to fundamental micro-structures in generic natural images and the basic elements in early (pre-attentive) visual perception. Overall, the new approach was able to achieve a high accuracy when applied to object, scene and landmark datasets.

With the current popularity of mobile devices, various types of mobile applications have been developed. Applications in the area of health have utilized hardware and software approaches such as cameras, sensors (accelerometers, gyroscopes, etc) and text messaging to improve health care of users [24]. Cameras have become standard in almost every mobile device sold today [25]. Mobile health applications have used cameras to provide nutritional information through augmented reality or recommend food intake [26], [27]. Modern mobile devices also have at least one type of built-in sensor. The device’s sensors are commonly used for a type of health application known as fitness applications [28]. These applications [29], [30] can provide information on the amount of physical activity performed, give exercise feedback and motivate the user to keep a regular exercise schedule. Text messaging is a basic service available on all types of mobile devices with subscriber identity module (SIM) card support and can be used to deliver simple and effective health services to users [31]. Health systems can use text messaging to send appointment reminders to users or provide a support system to patients [32], [33].

The use of these health applications does not necessarily need to be limited to sighted people. When object recognition is applied to faces, it can be used for identification. Face recognition is a suitable method for assisting visually impaired persons in identifying people compared to other biometric methods such as fingerprint, iris and voice recognition [34], [35], [36]. The advantages of face recognition over other approaches are passive recognition ability, fewer data acquisition errors and low implementation costs. Some areas where face recognition has been applied include electoral registration, identification cards, security, social networking and surveillance [36], [37].

With the rapid increase in computation power of mobile devices over the last decade, complex face recognition systems can be made portable. This paper proposes development of a face recognition system using a mobile device. The face recognition system captures images of a person’s face and matches it to faces in an existing database. Once a person is identified, the user of the mobile application is informed. The paper gives a framework of the overall system design and then gives a simple prototype implementation using built-in algorithms from the Open Source Computer Vision Library (OpenCV) [38]. This prototype system is then evaluated by conducting various tests. It also demonstrates the integration of OpenCV1 with the Android [40] mobile operating system and the Android application called TalkBack [41] which is used by visually impaired persons. The proposed system is designed to work on different mobile devices that include tablets and smartphones.

The rest of the paper is organised as follows. Background information is reviewed in Section 2 of the paper while Section 3 discusses the system’s design. Section 4 provides development results, testing results and implementation details of the system. Implementation issues and limitations of the system are discussed in Section 5. Finally, the paper is concluded in Section 6 with a description of future work.

II. BACKGROUND

A. Assistive Systems

There are many assistive systems in existence which are designed help visually impaired people. The most common type of system are those that provide navigation [14], [42]. A navigation and location determination system for the blind using an RFID tag grid was presented in [6]. The system consisted of RFID tags programmed with coordinates and descriptions of the surroundings. A mobile device was used to perform computational operations while a RFID reader integrated into a walking cane and shoe read RFID tags. This configuration had the advantage of not having to rely on a database or wireless infrastructure for access to information.

In [14], a different approach to navigation was proposed. Researchers used a depth estimation technique from a single image based on local depth hypothesis. Their approach used a camera to capture an image of the environment in front of the user. After the image was captured, obstacles were then isolated using edge detection and morphological operations. Next, the depth was estimated for each obstacle using local depth hypothesis. Afterwards, the estimated depth map was compared with the reference depth map of the corresponding depth hypothesis. Finally, the difference between the estimated and reference depth map was used to retrieve spatial information about the obstacles ahead of the user.

Moreover, a contextual information system for hearing and vision impaired people was presented in [8]. The system, known as Talking Points, provided contextual information about points of interest (POI) along a person’s route. It consisted of a mobile device for accessing information, an online database for storing POI information, POI tags (Bluetooth beacons) and software with graphical and speech interfaces. A mobile device allowed easy access to information from the online database and precise detection of POI tags through the built-in Bluetooth interface. Addition of new content and updates to the online database were done by community contributors.

In addition to navigation systems, there are also assistive systems which detect objects. A wearable obstacle detection system was proposed in [7]. This system was fully integrated into clothing for ease of use and consisted of ultrasonic sensors, vibration motors, power supplies and a micro-controller. The two main features of the system were detection of obstacles using sensors and guiding the user through an algorithm based on a neuro-fuzzy controller.

Another system enabled vision impaired users to play video games [43]. The system used real-time video analysis to detect visual cues in a gesture-based video game and provided users with vibrotactile cues instead. Video feed from the game was sent to a laptop computer which utilized Extensible Markup Language (XML) for storing a database of video games and providing users with guidance through sound.
Language (XML) based configuration files for determining the location of visual cues. Studies carried out by the researchers showed no major difference in performance between sighted and vision impaired players.

Some implementations combine navigation and detection of objects to create advanced assistive systems. An example of such a system is the SmartVision prototype [13]. This low cost navigation aid was designed to complement the use of white canes through the use of mobile devices. The system detected objects, obstacles and paths through a combination of a computer vision, Geographic Information System (GIS), GPS and Wi-Fi. These modules were used to track the user’s current location, plan routes and provide information about nearby POI. This system was further enhanced by the Nav4B prototype which used RFID tags to address the limitations of the SmartVision system [9].

A successor to the SmartVision navigation aid was developed by the authors in [42] as part of the Blavigator project. The new system added detection of doors in corridors and a sound interface in addition to existing features. The sound interface assisted users by guiding them to the center of paths and alerting them to approaching obstacles. For outdoor navigation, the authors implemented two layer obstacle detection and avoidance [44]. The first layer was used for object detection while the second provided trajectory correction and backup. With the use of stereo vision, the authors implemented range image segmentation to extract information for object detection and recognition.

B. Mobile Application Testing

One of the key challenges of mobile application testing is performing tests on different devices since they differ in hardware configuration [45]. Some differences include processors (dual-core, quad-core, hexa-core or octa-core), memory (512 MB, 1 GB, etc.), storage space (4 GB, 8 GB, etc.), input methods (touch screen or physical keypad), hardware sensors and screens with different display technologies.

The operating system of mobile devices also presents a challenge in testing because applications are handled differently by each operating system. For instance, an application may be easier to test on the Android operating system due to its open-source nature [46]. Another difficulty faced in mobile application testing is availability of resources. Applications can behave differently when resources such as memory, battery or network connectivity are limited or unavailable.

Mobile applications are often tested by developers in two stages [45]. In the first stage, the application is tested on the development machine using emulators. This allows the developers to quickly detect and correct implementation errors while the application is being developed. After testing on emulators, the application is tested on a real device in the second stage to ensure compatibility.

Another approach to testing mobile application is the use of specialized testing software. These software simplify the testing process by gathering information on specific components or automating specific tests. An example of a testing framework for mobile devices was proposed in [47]. The framework, known as Flying Emulator, introduced a mobile agent-based emulator of a mobile device. It performed application-transparent emulation of a mobile application written in Java for a specific device. Since the emulator is a mobile agent, it can test the application in the environments of different networks. Authors in [48], presented a tool for supporting automatic black-box testing of mobile applications. The tool known as MobileTest used a sensitive-event based approach to simplify design of test cases, increase testing efficiency and reusability. Experiments conducted by the authors on three different phone models showed the tool to be effective.

Furthermore, researchers in [49] proposed a test automation approach for addressing Android-specific bugs with a focus on those that affect the GUI. They collected and categorized bugs from 10 popular open-source Android applications. They observed that while bugs related to application logic were still present, the rest of the bugs were specific to the Android platform due to their general structure. The test approach created by the researchers combined automatic event and test case generation with runtime monitoring and log file analysis. Results showed the technique to be effective for activity, event and type errors. In [50], an approach for automation of mobile application testing was presented. It consisted of a Domain-Specific Modelling Language (DSML) known as MATEL (Mobile Applications Testing Language), a pre-existing test bed and its software infrastructure. MATEL allowed description of test scenarios where similarities and differences between mobile phones could be clearly expressed. This allowed easy testing on different phone models.

III. PROPOSED SYSTEM DESIGN

Identification of people is a major challenge faced by the visually impaired. The increase in computation capability of mobile devices gives motivation to develop applications that can assist visually impaired persons. The proposed face recognition system is designed to take advantage of the portability of mobile devices and provide a simple user interface that makes use of the system easy for the visually impaired. Key design requirements for a portable system include small device size and low weight. To achieve this goal, a wearable camera, mobile device and earpiece are used to form a compact and lightweight system (Fig 1). In order to provide a convenient software experience for the portable system, a straightforward application in a preferably familiar operating system is needed. The Android operating system allows a user-friendly application to be developed through the use of built-in accessibility features.

A. Software

1) Mobile Application: The face recognition application features two states of operation: offline and online. These states correspond to the absence and presence of an internet connection respectively. When in the offline state, the application accesses the video feed from the wearable camera through a Wi-Fi connection. This video feed is then scanned to detect faces. When a face is detected, a temporary image is captured and saved on the device. After the image is saved, it is used to identify the person by searching for a possible match in the application’s internal database. As soon as the person is identified, the result is displayed to the user. When the application is in the online state, the video feed is still
accessed for scanning and detecting faces. A temporary image is captured and saved when a face is detected in the same manner as in offline state. However, instead of attempting to identify the person, the image is sent to the cloud servers for identification. After the person is identified, the results are sent back to the application and displayed to the user.

Furthermore, the application allows a new person to be added to its internal face database via an option known as Enrolment Mode. The internal database consists of a SQLite [51] database and face images. Each face image is associated with one entry in the SQLite database. This internal database is also limited to the most frequently used faces for recognition.

The number of faces to store in the database is defined by the user. In Enrolment Mode, instead of performing identification after an image is captured, a new interface is displayed asking the user to enter details of the person. Upon entering the details of the person, their face is added to the database. The face detection and recognition features of the application are divided into two modules: Detection System and Recognition System.

a) Detection System: The main goal of the detection system in the application is to detect faces. When a face is detected, a bounding box is drawn around it (Fig 2). This bounding box is used to extract and save the face of a person by cropping the area inside it. Faces detected by the system are limited to frontal faces since the application is designed to identify persons in front of the user.

Detection is accomplished through the use of the object detector built into the OpenCV Android library [52]. The object detector uses a cascade classifier to detect faces. The cascade classifier is made up of a cascade of boosted classifiers with Haar-like features [53]. This machine learning based approach consists of a cascade function trained from a dataset of positive and negative images. In the case of face recognition, the positive images those which contain faces while the negative images are made of objects that are not faces. Haar feature-based cascade classifiers are a fast and effective method [53] of face detection suitable for use on modern mobile devices given their increasing computation power.

The cascade in cascade classifier refers to the resulting classifier created from many smaller classifiers (known as stages) which are applied sequentially to a specific region [54]. Boosted classifiers refer to classifiers at each stage of the cascade which are created from simple classifiers using a boosting technique [55]. Boosting is an algorithm for reducing bias in supervised learning. It works by combining weak classifiers to create a strong classifier.

b) Recognition System: The recognition system (Fig 3) complements the detection system by identifying the person using the detected face. This is done by running the recognition program which searches the internal database for a match using the saved face image as input. The recognition program utilizes C++ functions from the OpenCV library to identify people. This is due to limited support for Java-based face recognition in the OpenCV Android library. To enable use of
the C++ functions, the Java Native Interface\(^2\) (JNI) is used by the application.

The recognition program uses the Local Binary Patterns Histograms (LBPH) algorithm to perform recognition. It uses the Local Binary Patterns (LBP) method which creates a summary of the local structure in an image by comparing each pixel with its neighbours \([56]\). If the intensity of the centre pixel is greater or equal to its neighbour, it is assigned a value of 1 or 0 if not. The resulting binary numbers for each pixel are called Local Binary Patterns. To integrate this with face recognition, the LBP image is divided into local regions and a histogram is extracted from each image. The feature vector is then obtained by concatenating the local histograms. These histograms are called Local Binary Patterns Histograms. The use of the LBPH approach allows for fast feature extraction \([56]\).

2) Cloud Servers: The cloud servers in the face recognition system refer to a cloud-based support system for the mobile application. They enable enrolment and identification of individuals through the mobile device’s internet connection. This is accomplished by sending captured images and relevant information to the servers instead of processing it locally on the device. The implementation of cloud support permits use of the application on low specification devices which do not have powerful hardware required for real-time face recognition. Lastly, the use of a cloud based system can result in power savings on low and high specification devices since computational load is reduced \([57]\).

B. Hardware

The face recognition system consists of four hardware components; a wearable camera, an Android device, internet infrastructure and cloud servers (Fig 4). The wearable camera is a miniature device with imaging, video recording and Wi-Fi capabilities. This is accessed by an Android device through a Wi-Fi connection. For Internet access, a mobile network data connection is used. The configuration of the cloud servers depend on their implementation.

In the offline state, the application uses the video feed from the camera to detect and recognise faces. This is done in real-time using a device which can provide the necessary computation power. The prototype in this paper used an Android phone with a quad-core processor. While computation power requirements of mobile devices can be satisfied, the application will still be limited in operation time due to battery capacity.

Energy efficiency can increased by using context-aware power management techniques which alert the user if the device may run out of power before the next charging opportunity \([58]\). Moreover, the type of display a device has also determines power consumption with some displays being more energy efficient than others \([59]\). For visually impaired users, the display on devices can be dimmed to the lowest level or turned off in some cases to further increase power savings since displays consume a significant amount of power \([60]\).

IV. RESULTS AND IMPLEMENTATION

The prototype system proposed in this paper shows how face recognition can be used to assist visually impaired persons. This section highlights the major components of the system, discusses the person identification process and presents results of experiments conducted on the system showing good accuracy. Furthermore, tests on the mobile device and its results are also discussed.

The mobile application consists of four major components as shown in Fig 5. These are the OpenCV Java Module, User Interface, Android Module and OpenCV C++ Module. The OpenCV Java Module consists of the Detection System and functions for interfacing with the Android Module. Relevant functions and layouts make up the User Interface while the Android Module comprises of functions which manage the internal face database, interface with both OpenCV modules and handle overall operation of the application. Lastly, the OpenCV C++ Module comprises of the Recognition System and methods for interfacing with the Android Module.

The application interacts with three other components within the operating system to accomplish face recognition. These are the Camera Feed, Internet Connection and TalkBack (Google TalkBack is an accessibility service created by Google to assist visually impaired users with device interaction \([41]\). It adds spoken, audible and vibration feedback to a device.). When the application is launched, the video feed from the device’s camera is given to the OpenCV Java Module to perform face detection. After a face is detected, the OpenCV C++ Module is used to carry out face recognition. Once face recognition is complete, the results are conveyed to the user through the Android Module. Throughout the use of the application, TalkBack is used to provide audible information to the users allowing them to operate the application with limited sight.

A. Prototype: Simulation and Experiments

The mobile application was tested on a custom video database with a total of 8 videos. Each video was recorded using a mobile phone camera at a resolution of 1280 x 720 at 30 fps. All videos were taken at evening in artificial lighting conditions with variations in face orientations. The experiments were divided into two sections; Face Detection and Face Recognition with a total of 80 experiment runs for face detection and 50 experiment runs for face recognition respectively.

1) Face Detection: The results for face detection show detection accuracy of up to 93% in well-lit conditions as shown in Table 1. Better detection accuracy was achieved when the person is looking directly at the camera with a neutral facial

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\(^2\)http://docs.oracle.com/javase/7/docs/technotes/guides/jni/
expression (Videos 1, 3 and 6). Lower accuracy is obtained when faces are detected at slight angles and different facial expressions are used (Videos 2, 4, 5 and 8). An ideal accuracy (Video 7) can be obtained when the person is walking directly toward the camera. This occurs when no false detections are made due to a simple background with no other objects. The result however is only possible when the user is stationary and ideal conditions are present. Computation times for each frame, whether a face was present or not, were less than 400 ms.

| Video | Frames with Faces | Detections | Correct | Incorrect | Accuracy (%) |
|-------|-------------------|------------|---------|-----------|--------------|
| 1     | 130               | 17         | 15      | 2         | 88.24        |
| 2     | 67                | 16         | 14      | 2         | 87.50        |
| 3     | 82                | 15         | 14      | 1         | 93.33        |
| 4     | 79                | 18         | 15      | 3         | 83.33        |
| 5     | 116               | 24         | 17      | 7         | 70.83        |
| 6     | 270               | 19         | 17      | 2         | 89.47        |
| 7     | 102               | 10         | 10      | 0         | 100.00       |
| 8     | 139               | 8          | 7       | 1         | 87.50        |

2) Face Recognition: Table II shows the results for face recognition which were obtained by feeding the results of face detection into the recognition program. However, only true detections (where an actual face was detected) were considered. Results for face recognition show relatively high recognition accuracy for Persons 1 and 4. This is possibly due to the person looking almost directly at the camera with a neutral face expression. Face recognition accuracy for Persons 2 and 3 are lower as a result of recognising faces at angles with different facial expressions. A major factor in low recognition accuracy is the use of only frontal face images for enrolling a person into the face database. These results indicate that further improvements to the face recognition program are required.

| Person | Experiments | Correct | Incorrect | Accuracy (%) |
|--------|-------------|---------|-----------|--------------|
| 1      | 32          | 18      | 64.00     |
| 2      | 50          | 26      | 24        | 52.00        |
| 3      | 29          | 21      | 58.00     |
| 4      | 35          | 15      | 70.00     |

B. Mobile Device Testing

1) Test Setup: Battery usage is one of the most important factors in the performance of the face recognition application. Several components of the device are used when the application is in operation. Firstly, the application constantly receives frames from the video feed of the external camera where energy is drained by the wireless connection. Processing these frames to detect and recognise faces is also computationally expensive which further drains energy. Thirdly, energy is drained by the data connection when the cloud server is used to recognise faces. Lastly, feedback provided to the user on application navigation and recognition results continuously drains energy. The battery use by the device is analysed by running the application and using Android’s built-in battery application to get the power consumption. The power consumption from the battery application is verified using the Android Debug Bridge (ADB) [61].

The impact on processing power by the face recognition application is analysed next. This is done by measuring the processor use through the ADB when the application is running (attempting to detect faces) and performing face recognition. Another factor which affects the performance of the application is memory use. The memory use is also measured by the ADB under the same scenarios as the processor use.

Analysing data use by the application is important since the use of mobile data can be expensive for the user. Data usage from performing cloud-based face recognition is measured using the built-in data monitoring application of the operating system and verified through the ADB.

2) Testing Results:

a) Battery: Battery usage by the device when the mobile application is running is shown in Table III. The mobile face recognition application accounts for 36% of total battery used by the device. Energy used by the mobile network is 24% of the total battery use while the Wi-Fi connection uses 13%. The media server of the device uses the least energy at 3%. Finally, a significant amount of energy (24%) is used by the device when it is idle. This is due to some cores of the
processor being idle while the application is running. These idle cores can allow the user to use other applications without needing to close the face recognition application for processing power.

TABLE III. BATTERY USAGE PROFILE OF THE DEVICE

| Time Elapsed | Battery Life (%) | Battery Usage (%) |
|--------------|------------------|-------------------|
|              | App | Mobile Standby | Phone Idle | Wi-Fi | Media Server |
| 10 mins      | 95  |                |            |       |              |
| 20 mins      | 92  |                |            |       |              |
| 30 mins      | 90  |                |            |       |              |
| 45 mins      | 84  | 36             | 24         | 24    | 13           |
| 1 hr 10 mins | 76  |                |            |       |              |
| 1 hr 25 mins | 71  |                |            |       |              |
| 1 hr 30 mins | 68  |                |            |       |              |

b) Processing Power & Memory: The processing power (CPU %) used by the application is shown in Fig 6. It shows 31 filtered entries taken by the ADB at 1 second intervals on a console. The minimum CPU use by the application is 59%, the maximum is 65% and the average use is 62%. Memory use by the application is shown in Fig 7. The private memory use (i.e. used by the application only) is shown to be 11.488 MB. This indicates that the application is not memory intensive.

c) Data Usage: The application does not use a large amount of data since most of the data sent and received consists of text and small images which are less than 100 kb. Data use when fully syncing a face database for one user account is shown in Fig 8. This full sync consists of 10 greyscale face images which have an average size of 20 kb and related text data on the person that each face represents.

V. DISCUSSION

The mobile face recognition system was implemented on a 3G Android device with a 1.3 GHz quad-core processor and an 1800 mAh battery running Android 4.2.2 [62]. These specifications allow the device to process several video frames in real-time while maintaining application response. This device was connected to a wearable camera which provided a 640 x 480 video feed through Wi-Fi. Major components of the mobile application included the OpenCV Java Module, User Interface, Android Module and OpenCV C++ Module. The face detection system was part of the OpenCV Java Module (to avoid increasing overhead from JNI calls when using C++ functions of OpenCV) while the recognition system was part of the OpenCV C++ Module. Finally, cloud servers supported the application by providing fast enrolment and identification of people.

Deploying the mobile face recognition system for actual use will have challenges. A major concern is battery life of mobile devices since real-time computer vision constantly uses hardware resources. While the ability to offload computation tasks to the cloud servers can conserve power, this can lead to increased costs for the user due to the use of mobile data. In real world deployment of the system, users may need to undergo training. Users may not be familiar with using an application while TalkBack is enabled. A tutorial is built into TalkBack for training users on how to use the application. Regarding maintenance, the application does not require any as redundant files are automatically deleted. However, the cloud servers may need an administrator to manage the face database when it grows to a very large size.

Security is a potential problem for the face recognition system. The most important area of concern in security is the face images of people and their identity. To ensure that these are protected, the face images are stored in a location accessible only to the application while the identities of people are stored in an encrypted format. The use of face recognition also creates a privacy issue since face images of people are used when performing recognition and enrolling individuals. To address this, the system captures a temporary image when performing recognition and stores face images in a folder only accessible by the application for enrolment. Once the recognition is complete or the internal database is updated with enrolled individuals, the face images are deleted in each case.

The mobile application was tested on a custom video database comprising of 8 videos with resolution of 1280 x 720 at 30 fps. A maximum face detection accuracy of 93% and face recognition accuracy of 70% were achieved in well-lit conditions.

In the current implementation, the face detection program is limited to only well-lit conditions. Experiments were conducted using poorly-lit versions of some videos from the custom database resulting in poor detection rates. The absence
of a large amount of light makes it difficult for the detector to correctly detect faces. Also, the test video database is small and limited to a few faces.

A future extension to the mobile application can assist sighted persons as well through the use of a zooming feature. A zooming feature can be used as a substitute for reading glasses by enlarging written text through the device’s camera and displaying them to the user. Furthermore, the face detection program can be further refined to work in poorly-lit conditions. The recognition process can also be improved by using three dimensional (3D) object recognition [63] techniques to retrieve better facial features from people. The test video database could also be expanded to include more faces under different lighting and weather conditions.

VI. CONCLUSION

This paper discussed the development of a mobile based face recognition system. A wearable camera was used for image acquisition while an Android application processed the image. The application featured a face detection and recognition program.

The face detection program detected faces from the video feed using a cascade classifier. Once a face was detected, it was recognised using a temporary image of the detected face. Google TalkBack was used to provide users with feedback on the operation of the application. Experiments showed a face detection accuracy of 93% and face recognition accuracy of 70% in well-lit conditions. The performance of the mobile application was also evaluated by conducting tests on the mobile device. Results show low memory and data usage as strengths of the system while limitations include energy use and processing power.

Future work will focus on improving the detection and recognition systems. The detection system can be further improved by training a new cascade classifier for the face detector while a neural network based program can be used to improve the recognition system. Wearable devices such as smartwatches could also improve the system by making it easier for the user to interact with the mobile application.

REFERENCES

[1] WHO. (2013, October) Visual impairment and blindness. Archived at http://www.webcitation.org/6MRAVQQqD. [Online]. Available: http://www.who.int/mediacentre/factsheets/fs282/en/
[2] K. Boerner and V. Cimarolli, “Social support and well-being in adults who are visually impaired,” Journal of Visual Impairment & Blindness (JVIB), vol. 99, no. 09, 2005.
[3] C. Y. Wan, A. G. Wood, D. C. Reutens, and S. J. Wilson, “Early but not late-blindness leads to enhanced auditory perception,” Neuropsychologia, vol. 48, no. 1, pp. 344 – 348, 2010.
[4] National Federation of the Blind. (2014) Free white cane program. [Online]. Available: https://nfb.org/free-cane-program
[5] F. Gougoux, P. Belin, P. Voss, P. Lepore, M. Lassonde, and R. J. Zatorre, “Voice perception in blind persons: A functional magnetic resonance imaging study,” Neuropsychologia, vol. 47, no. 13, pp. 2967 – 2974, 2009.
[6] S. Willis and S. Helal, “Rfid information grid for blind navigation and wayfinding,” in ISWC, vol. 5, 2005, pp. 34 – 37.
[7] S. K. Bahadir, V. Koncar, and F. Kalaoglu, “Wearable obstacle detection system fully integrated to textile structures for visually impaired people,” Sensors and Actuators A: Physical, vol. 179, no. 0, pp. 297 – 311, 2012.
Fig. 7. Memory used by the application.

![Memory used by the application]

Fig. 8. Data used by the application.

![Data usage]

[8] J. Stewart, S. Bauman, M. Escobar, J. Hilden, K. Bihani, and M. W. Newman, “Accessible contextual information for urban orientation,” in Proceedings of the 10th International Conference on Ubiquitous Computing, ser. UbiComp’08. New York, NY, USA: ACM, 2008, pp. 332 – 335.

[9] H. Fernandes, V. Filipe, P. Costa, and J. Barroso, “Location based services for the blind supported by rfid technology,” Procedia Computer Science, vol. 27, no. 0, pp. 2 – 8, 2014, 5th International Conference on Software Development and Technologies for Enhancing Accessibility and Fighting Info-exclusion, {DSAI} 2013.

[10] J. Falco, M. Idiago, A. Delgado, A. Marco, A. Asensio, and D. Cirujano, “Indoor navigation multi-agent system for the elderly and people with disabilities,” in Trends in Practical Applications of Agents and Multiagent Systems, ser. Advances in Intelligent and Soft Computing, Y. Demazeau, F. Dignum, J. Corcho, J. Bajo, R. Corchuelo, E. Corchado, F. Fernández-Riverola, V. Julin, P. Pawlewski, and A. Campbell, Eds. Springer Berlin Heidelberg, 2010, vol. 71, pp. 437–442.

[11] P. Dudas, M. Ghafoorian, and H. Karimi, “Onalin: Ontology and algorithm for indoor routing,” in Mobile Data Management: Systems, Services and Middleware, 2009. MDM’09. Tenth International Conference on, May 2009, pp. 720–725.

[12] V. Chawla and D.-S. Ha, “An overview of passive rfid,” Communications Magazine, IEEE, vol. 45, no. 9, pp. 11–17, September 2007.

[13] J. M. H. du Buf, J. Barroso, J. M. F. Rodrigues, H. Paredez, M. Farrajota, H. Fernandes, J. José, V. Teixeira, and M. Saleiro, “The smartvision navigation prototype for blind users,” in JDICTA: International Journal of Digital Content Technology and its Applications, 2011, p. 361.

[14] R. G. Praveen and R. P. Paily, “Blind navigation assistance for visually impaired based on local depth hypothesis from a single image,” Procedia Engineering, vol. 64, no. 0, pp. 351 – 360, 2013, international Conference on Design and Manufacturing (ICONDm2013).

[15] R. Jain, R. Kasturi, and B. G. Schunck, Machine Vision. McGraw-Hill New York, 1995, vol. 5, ch. 15.

[16] H. S. Al-Khalifa, “Utilizing qr code and mobile phones for blinds and visually impaired people,” in Proceedings of the 11th International Conference on Computers Helping People with Special Needs, ser. ICCHP ’08. Berlin, Heidelberg: Springer-Verlag, 2008, pp. 1065 – 1069.

[17] Y. Tian, X. Yang, and A. Arditi, “Computer vision-based door detection for accessibility of unfamiliar environments to blind persons,” in Proceedings of the 12th International Conference on Computers Helping People with Special Needs, ser. ICCHP’10. Berlin, Heidelberg: Springer-Verlag, 2010, pp. 263 – 270.

[18] J. C. Lierer and H. H. Bülthoff, “An introduction to object recognition,” Zeitschrift für Naturforschung C-Journal of Biosciences, vol. 53, no. 7, pp. 610 – 621, 1998.

[19] M. A. Treiber, An Introduction to Object Recognition: Selected Algorithms for a Wide Variety of Applications, 1st ed. Springer Publishing Company, Incorporated, 2010.

[20] S. Palanivel and B. Yegnanarayana, “Multimodal person authentication using speech, face and visual speech,” Computer Vision and Image Understanding, vol. 109, no. 1, pp. 44 – 55, 2008.

[21] L. Nanni and A. Luminii, “Heterogeneous bag-of-features for object/scene recognition,” Applied Soft Computing, vol. 13, no. 4, pp. 2171 – 2178, 2013.

[22] L. Nanni, S. Brahnam, and A. Luminii, “Random interest regions for object recognition based on texture descriptors and bag of features,” Expert Syst. Appl., vol. 39, no. 1, pp. 973 – 977, Jan. 2012.

[23] Y. Ke and R. Sukthankar, “Pca-sift: A more distinctive representation for local image descriptors,” in Proceedings of the 2004 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, ser. CVPR’04. Washington, DC, USA: IEEE Computer Society, 2004, pp. 506 – 513.

[24] P. Klasnja and W. Pratt, “Healthcare in the pocket: Mapping the space of mobile-phone health interventions,” Journal of Biomedical Informatics, vol. 45, no. 1, pp. 184 – 198, 2012.

[25] S. Bourke, K. McCarthy, and B. Smyth, “The social camera: A case-study in contextual image recommendation,” in Proceedings of the 16th
M. Z. Bayu, H. Arshad, and N. M. Ali, “Nutritional information visualization using mobile augmented reality technology,” *Procedia Technology*, vol. 11, no. 0, pp. 396 – 402, 2013, 4th International Conference on Electrical Engineering and Informatics, [ICEEI] 2013.

F. Kong and J. Tan, “Dietcam: Automatic dietary assessment with mobile camera phones,” *Pervasive and Mobile Computing*, vol. 8, no. 1, pp. 147 – 163, 2012.

F. Buttussi, L. Chittaro, and D. Nadalulti, “Bringing mobile guides and fitness activities together: A solution based on an embodied virtual trainer,” in *Proceedings of the 8th Conference on Human-computer Interaction with Mobile Devices and Services*, ser. MobileHCI ’06. New York, NY, USA: ACM, 2006, pp. 29 – 36.

M. Kranz, A. Miller, N. Hammerla, S. Diewald, T. Pitz, P. Olivier, and L. Roalter, “The mobile fitness coach: Towards individualized skill assessment using personalized mobile devices,” *Pervasive and Mobile Computing*, vol. 9, no. 2, pp. 203 – 215, 2013, special Section: Mobile Interactions with the Real World.

S. Consolvo, K. Everitt, I. Smith, and J. A. Landay, “Design requirements for technologies that encourage physical activity,” in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, ser. CHI ’06. New York, NY, USA: ACM, 2006, pp. 457 – 466.

A. Waller, V. Franklin, C. Pagliari, and S. Greene, “Participatory design of a text message scheduling system to support young people with diabetes,” *Health Informatics Journal*, vol. 12, no. 4, pp. 304 – 318, 2006.

K. Fairhurst and A. Sheikh, “Texting appointment reminders to repeated non-attenders in primary care: randomised controlled study,” *Quality and Safety in Health Care*, vol. 17, no. 5, pp. 373 – 376, 2008.

V. L. Franklin, A. Waller, C. Pagliari, and S. A. Greene, “A randomized controlled trial of sweet talk, a text-messaging system to support young people with diabetes,” *Diabetic Medicine*, vol. 23, no. 12, pp. 1332 – 1338, 2006.

A. Jain, A. Ross, and S. Prabhakar, “An introduction to biometric recognition,” *Circuits and Systems for Video Technology, IEEE Transactions on*, vol. 14, no. 1, pp. 4 – 20, Jan 2004.

J.-S. Kang, “Mobile iris recognition systems: An emerging biometric technology,” *Procedia Computer Science*, vol. 1, no. 1, pp. 475 – 484, 2010, ICCS 2010.

R. Jafri and H. R. Arabnia, “A survey of face recognition techniques,” *Journal of Information Processing Systems*, vol. 5, no. 2, pp. 41 – 68, 2009.

E. G. Ortiz and B. C. Becker, “Face recognition for web-scale datasets,” *Computer Vision and Image Understanding*, vol. 118, no. 0, pp. 153 – 170, 2014.

OpenCV Developers Team. (2014) [OpenCV | OpenCV]. [Online]. Available: http://opencv.org/

--- (2014) ABOUT | OpenCV. [Online]. Available: http://opencv.org/about.html

Google Inc. (2014) Android. [Online]. Available: https://www.android.com/

--- (2014) Google TalkBack. [Online]. Available: https://play.google.com/store/apps/details?id=com.google.android.marvin.talkback&hl=en

M. Moreno, S. Shahrahadi, J. José, J. du Buf, and J. Rodrigues, “Realtime local navigation for the blind: Detection of lateral doors and sound interface,” *Procedia Computer Science*, vol. 14, no. 0, pp. 74 – 82, 2012, proceedings of the 4th International Conference on Software Development for Enhancing Accessibility and Fighting Info-exclusion (DSAI 2012).

T. Morelli and E. Folmer, “Real-time sensory substitution to enable players who are blind to play video games using whole body gestures,” *Entertainment Computing*, vol. 5, no. 1, pp. 83 – 90, 2014.

P. Costa, H. Fernandes, P. Martins, J. Barroso, and L. J. Hadjileontiadis, “Obstacle detection using stereo imaging to assist the navigation of visually impaired people,” *Procedia Computer Science*, vol. 14, no. 0, pp. 83 – 93, 2012, proceedings of the 4th International Conference on Software Development for Enhancing Accessibility and Fighting Info-exclusion (DSAI 2012).

D. Amalfitano, A. R. Fasolino, P. Tramontana, and B. Robbins, “Testing android mobile applications: Challenges, strategies, and approaches.” *Advances in Computers*, vol. 89, pp. 1–52, 2013.

C. Ntantogian, D. Apostolopoulos, G. Marinakis, and C. Xenakis, “Evaluating the privacy of android mobile applications under forensic analysis,” *Computers & Security*, vol. 42, no. 0, pp. 66 – 74, 2014.

I. Satoh, “A testing framework for mobile computing software,” *IEEE Trans. Softw. Eng.*, vol. 29, no. 12, pp. 1112 – 1121, Dec. 2003.

J. Bo, L. Xiang, and G. Xiaopeng, “Mobiletest: a tool supporting automatic black box test for software on smart mobile devices,” in *Proceedings of the Second International Workshop on Automation of Software Test*. IEEE Computer Society, 2007, p. 8.

C. Hu and I. Neamtiu, “Automating gui testing for android applications,” in *Proceedings of the 6th International Workshop on Automation of Software Test*, ser. AST ’11. New York, NY, USA: ACM, 2011, pp. 77 – 83.

Y. Ridene and F. Barbier, “A model-driven approach for automating mobile applications testing,” in *Proceedings of the 5th European Conference on Software Architecture: Companion Volume*, ser. ECSA ’11. New York, NY, USA: ACM, 2011, pp. 9:1–9:7.

SQLite Development Team. (2014) About sqlite. [Online]. Available: https://www.sqlite.org/about.html

OpenCV Developers Team. (2014) ANDROID | OpenCV. [Online]. Available: http://opencv.org/platforms/android.html

P. Viola and M. Jones, “Rapid object detection using a boosted cascade of simple features,” in *Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference on*, vol. 1. IEEE, 2001, pp. 511 – 518.

Z. Sun, Y. Wang, T. Tan, and J. Cui, “Improving iris recognition accuracy via cascaded classifiers,” *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, vol. 35, no. 3, pp. 435 – 441, Aug 2005.

R. E. Schapire, “The strength of weak learnability,” *Machine Learning*, vol. 5, no. 2, pp. 197 – 227, Jul. 1990.

T. Ahonen, A. Hadid, and M. Pietikäinen, “Face recognition with local binary patterns,” in *Computer Vision-ECCV 2004*. Springer, 2004, pp. 469 – 481.

A. P. Miettinen and J. K. Nurminen, “Energy efficiency of mobile clients in cloud computing,” in *Proceedings of the 2Nd USENIX Conference on Hot Topics in Cloud Computing*, ser. HotCloud’10. Berkeley, CA, USA: USENIX Association, 2010, pp. 4–4.

N. Ravi, J. Scott, L. Han, and L. Itode, “Context-aware battery management for mobile phones,” in *Proceedings of the 2008 Sixth Annual IEEE International Conference on Pervasive Computing and Communications*, ser. PERCOM ’08. Washington, DC, USA: IEEE Computer Society, 2008, pp. 224 – 233.

X. Chen, Y. Chen, Z. Ma, and F. C. A. Fernandes, “How is energy consumed in smartphone display applications?” in *Proceedings of the 14th Workshop on Mobile Computing Systems and Applications*, ser. HotMobile’13. New York, NY, USA: ACM, 2013, pp. 3:1–3:6.

A. Carroll and G. Heiser, “An analysis of power consumption in a smartphone,” in *Proceedings of the 2010 USENIX Conference on USENIX Annual Technical Conference*, ser. USENIXATC’10. Berkeley, CA, USA: USENIX Association, 2010, pp. 21–21.

Google Inc. (2014) Android debug bridge. [Online]. Available: https://developer.android.com/tools/help/adb.html

ZOPO. (2014) ZOPO ZP780. [Online]. Available: http://www.zopomobile.com/en/228-zopo-zp780-android-smart-phone.html

R. B. Gomes, B. M. F. da Silva, L. K. de Medeiros Rocha, R. V. Aroca, L. C. P. R. Velho, and L. M. G. Gonçalves, “Efficient 3d object recognition using foveated point clouds,” *Computers & Graphics*, vol. 37, no. 5, pp. 496 – 508, 2013.