A Wearable Face Recognition System on Google Glass for Assisting Social Interactions

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Abstract. In this paper, we present a wearable face recognition (FR) system on Google Glass (GG) to assist users in social interactions. FR is the first step towards face-to-face social interactions. We propose a wearable system on GG, which acts as a social interaction assistant, the application includes face detection, eye localization, face recognition and a user interface for personal information display. To be useful in natural social interaction scenarios, the system should be robust to changes in face pose, scale and lighting conditions. OpenCV face detection is implemented in GG. We exploit both OpenCV and ISG (Integration of Sketch and Graph patterns) eye detectors to locate a pair of eyes on the face, between them the former is stable for frontal view faces and the latter performs better for oblique view faces. We extend the eigenfeature regularization and extraction (ERE) face recognition approach by introducing subclass discriminant analysis (SDA) to perform within-subclass discriminant analysis for face feature extraction. The new approach improves the accuracy of FR over varying face pose, expression and lighting conditions. A simple user interface (UI) is designed to present relevant personal information of the recognized person to assist in the social interaction. A standalone independent system on GG and a Client-Server (CS) system via Bluetooth to connect GG with a smart phone are implemented, for different levels of privacy protection. The performance on database created using GG is evaluated and comparisons with baseline approaches are performed. Numerous experimental studies show that our proposed system on GG can perform better real-time FR as compared to other methods.

1 Introduction

Knowing the identity of a person is the first step in a face-to-face social interaction. When meeting an unknown or unfamiliar person, recognizing who he/she is and knowing the essential personal information about him/her, such as name, job and working company, can be very helpful in engaging with the person for an interaction or conversation. Sometimes it is embarrassing when we are unable to recall somebody's name with whom we have met and/or interacted for a sufficiently long time in the near past. Hence, it has become an interesting research topic on developing wearable systems that can aid visual memory to an individual, especially in remembering names or recognizing people with whom we meet/recall or have interests [1–3]. Such wearable system will also be very helpful to persons with difficulty in remembering and recognizing faces, such as some form of prosopagnosia [4] which causes difficulty in distinguishing facial features and differentiating people in their social lives [5–8].

With the emergence of popular wearable devices like Google Glass, it has become possible to develop wearable FR system for users as an online assistant for social interactions. We propose a real-time wearable FR system on GG that can recognize persons with various face poses under natural lighting conditions and provide essential personal information for social interactions. This helps to log interaction events automatically, remember names of the person and hence, acts as a memory aid and information service to an individual. One important capability of wearable FR for social interactions is the ability to recognize faces of various poses, scales and under varying lighting conditions. For example, before a formal face-to-face engagement, you may not have been able to capture a frontal view of the person from your view point. Next is that the user would prefer to perform FR locally, *e.g.* solely on GG or just connecting to the user's smartphone, because of the fact that the face and personal information are highly private. There are a few existing FR systems with GG, like NameTag [9], but they are not meant to be used as an online assistant for social interactions.

In this paper, we first enhance the face detection from OpenCV [10] for non-frontal views of faces. Next, we integrate two eye detectors, OpenCV [10] and ISG [11] eye detectors, for better performance on FPV videos. We improve the eigenfeature regularization and extraction (ERE) [12, 13] face recognition approach by introducing subclass discriminant analysis (SDA) [14] to perform whole space subclass discriminant analysis (WSSDA) for face feature learning and face recognition. We implement two architectures on GG, *i.e.* one local scheme solely on GG and another Client-Server scheme using Bluetooth to connect GG to the user's smartphone, for the tradeoff of computational burden on GG and privacy protection levels. Details of evaluations and comparisons with baseline approaches are presented.

The remainder of the paper is organized as follows. The next subsection discusses related work. The system configuration and modules on face detection, eye localization, face recognition, and implementations on GG are described in Section 2. The evaluation of performance for eye localization, face recognition and computational efficiency are presented in Section 3. Finally, conclusions and future work are discussed in Section 4.

1.1 Related Work

Face recognition (FR) is perhaps one of the most well studied computer vision research problems. Researchers from diverse areas have been studying problems associated with FR for over four decades [15]. Recently, good progress has been made in recognizing frontal face images with even lighting conditions and tolerance to large variations in expressions. However, the performance drops to a very large extent for changes with pose, uneven lighting conditions and ageing [16–18]. A systematic independent evaluation of recent face recognition algorithms from commercial and academic institutions can be found in the face recognition vendor test (FRVT) 2013 report [19].

There are a few systems proposed for wearable FR [1–3]. Krishna *et al.* [1], developed an iCare Interaction Assistant device for helping visually impaired individuals for social interactions. Their evaluations are limited to only 10 subjects' face images captured under tightly controlled and calibrated face images using classical subspace methodologies like principal component analysis (PCA) and linear discriminant analysis (LDA). Utsumi, *et al.* proposed a coarse-to-fine scheme for FR based on simple image matching [2]. In [3], a simple HMM model is used to capture engagement faces from online FPV videos. However, none of them has been implemented on GG.

Another eye wearable system for improving social lives of prosopagnosics is developed by Wang *et al.* [8]. This system enables prosopagnosic patients to identify the people they come across. Due to their high processing requirements, their modules run on a smartphone. The camera and display units are placed in the wearable eye glass (Vuzix STAR 1200XL third generation augmented reality device). For this system also, the performance evaluations are limited to 20 subjects using local binary pattern (LBP) features.

We propose and implement a FR system on GG with improved face detection, eye localization and face recognition for various face poses and lighting conditions naturally observed from FPV videos in social interactions.

2 The Proposed System

In this section, system configuration and implementation of the main modules are described.

2.1 System Overview

Fig. 1 shows the block diagram of our wearable FR system on GG for social interaction assistance. The input FPV image is captured by the camera in GG and then face detection is performed using OpenCV face detector. A pair of eyes are located by fusing the results from OpenCV eye detector [10] and ISG (integration of sketch and graph patterns) eye detector [11]. Using the detected eye coordinates, faces are aligned, normalized and cropped following the CSU Face Identification Evaluation System [20]. Normalized face image is used for FR. According to the FR result, the person is identified and his/her personal information is retrieved from the database. The most relevant personal information is displayed on the screen of GG to assist the user in social interaction.

Training for FR is performed using within-subclass based statistical learning method extended from [12, 13]. Low dimensional face discriminative features are extracted and stored in the database. Any incoming novel image is first

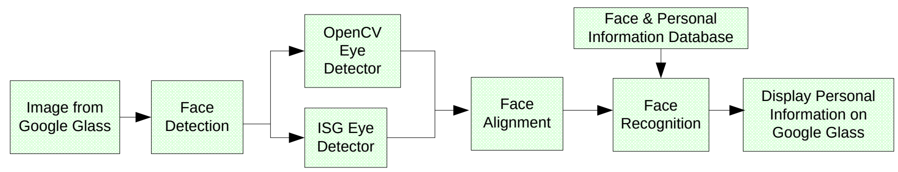

Fig. 1. Our algorithm design flow in Google Glass for face recognition.

converted into features and then compared against those stored in the database and a matching ID is obtained using minimum distance measure.

2.2 Face Detection and Eye Localization

The original API (application protocol interface) provided in GG allows us to capture images at 30 frames per second (fps). However, to reduce the computation burden on GG, we reduce the capturing rate to 5 fps. Firstly, OpenCV face detector [21] is applied to find faces in the incoming images. It is very robust in finding frontal faces, as it is trained with a huge number of training samples. However, it cannot detect faces with pose variations. In a ten-minute video recording of an interaction involving 3 people, the OpenCV detector can only detect about 40% of the faces in the poses of looking at the GG (frontal faces). At all other times it fails due to non-frontal view faces, motion blurry, severe shadows and other poor lighting conditions. Therefore, we train a new face detector specially for the non-frontal view faces using the OpenCV face detection algorithm, *i.e.*, the algorithm based on Harr features and Adaboost classifier [10]. Both face detectors are applied to find faces in the input image frame.

OpenCV eye detector [10] performs well to locate eyes in the front-view face images, even with closed eyes. But it often fails to locate the pair of eyes in an oblique-view face (poses other than frontal views) or face of smaller scale (people who are at far distances). To alleviate these problems, we use the ISG eye detector developed for human-robot-interaction in [11]. It is re-trained for detecting and locating a pair of open eyes in both frontal-view and oblique-view faces. It performs much better to detect and locate a pair of open eyes in oblique-view faces than the OpenCV eye detector. Also, using this eye detector, the correct detection rate is much higher for faces of small scales in the image compared to OpenCV eye detector. However, it might fail to find the correct locations of closed eyes. Through the integration of both eye detectors, we are able to achieve high success rate of eye localization in the face images of FPV for both frontal and non-frontal faces at various scales (sizes).

Using the eye coordinates, faces are aligned, eye coordinates are placed at fixed distances, cropped and re-sized to 67×75 pixels. We use the face normalization technique described in [20]. The images collected using GG are often blurry in nature as the person wearing the GG moves his/her head quite frequently. Also, sometimes the images are out of camera focus. The face and eye detectors also serve as filters to remove images with large motion blur or poor image quality.

2.3 Within-Subclass Subspace Learning for Face Recognition

To make natural social interactions online viable, the wearable system should be able to recognize person's faces with various poses and lighting conditions. Especially, recognizing a person's face and providing the related personal information, even before the person is engaged in the interaction process. In such situations, often the person has not directly faced the user yet, so no frontal view face image might be available to the user's FPV observations.

Traditional discriminant analysis employs between-class and within-class scatter information for face pattern classification [15]. When applied to uncontrolled illumination, expression and multi-pose FR, it may lose crucial discriminant information in individual's face images [22–25]. In this system, we propose to introduce the subclass discriminant analysis (SDA) [14] into existing subspace learning approach for FR.

In training stage, for each person enrolled in the database, seven face images of different poses, *e.g.* looking front, up, down, left and right, are collected. All these face images are normalized and preprocessed following the CSU Face Identification Evaluation System [20]. The training face images of each person are clustered into subclasses using mixture of Gaussians representation as done in [14]. Then, we compute the within-subclass scatter matrix. Eigenfeature regularization scheme [22] is applied to regularize features obtained from whole space within-subclass scatter matrix. On these regularized features, total-subclass and between-subclass scatter matrixes (depending on the clusters for each person and the number of people in the database [22, 26]) are computed. Finally, only those features are used for which the corresponding eigenvalues (variances) are largest.

This kind of regularized features are reported to perform better for both the tasks of FR, which are face identification (FI) [22] and face verification (FV) [12, 27] as compared to other subspace methods (like Eigenfaces [28], Fisherfaces [29], Bayesian FR [30, 31] and other variants of Fisherfaces [32–35]) and local features [36]. Particularly, we selected this method because the features obtained are optimal as they are extracted after the whole space discriminant analysis [22]. Also, this method achieves good recognition rates with very small number of features [22, 23]. The proposed method is named as whole space subclass discriminant analysis (WSSDA) for FR. The proposed method has been evaluated on the challenging YouTube face (YTF) database following the existing protocol for FR [37]. Fig. 2 shows the average receiver operating characteristics (ROC) curves that plots the true acceptance rate (TAR) against the false acceptance rate (FAR) following the 10-fold cross-validation pairwise tests protocol suggested for the YTF database [37]. It can be seen that our method performs better among the popular baseline approaches like mixture discriminant analysis

(MDA) [38], SDA [14], mixture subclass discriminant analysis (MSDA) [39] and ERE [22, 23] for FV task.

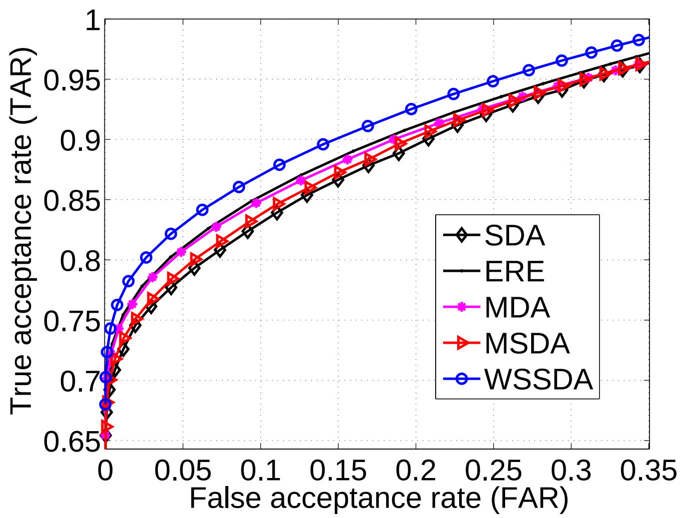

Fig. 2. Average of 10-folds of cross-validation ROC curves plotting true acceptance rate against the false acceptance rate on YouTube database [37] (best viewed in color).

After training, only the gallery features and transformation matrix are stored in the system. When more people have to be enrolled in the database, the incoming face images are transformed using the above generated training module (transformation matrix) and only the gallery features are stored.

In recognition stage, any incoming face image vector is converted into a feature vector using the transformation matrix learned by WSSDA method. The feature vector is used to perform recognition by matching it with the gallery features. We use cosine distance measures with 1-nearest neighbor (NN) as the best match for each of the faces in a frame.

2.4 User-Interface Design

The resolution of GG's display is of 640×360 pixels. Keeping the small display resolution in mind, we design a simple user interface with large fonts of brief description of personal information. Another consideration for designing a simple interface is to cause less distraction to the natural social interactions. The app interface has three main components: (i) an option menu to trigger the start of recognition, (ii) a guided viewfinder for positioning of the portrait face and (iii) a three-page display showing the personal information of the recognized person, as shown in Fig. 3. App navigation and control is performed via touch gesture: (1) menu options are activated and canceled by tapping and swiping down respectively and (2) navigation is done by swiping to the left or right.

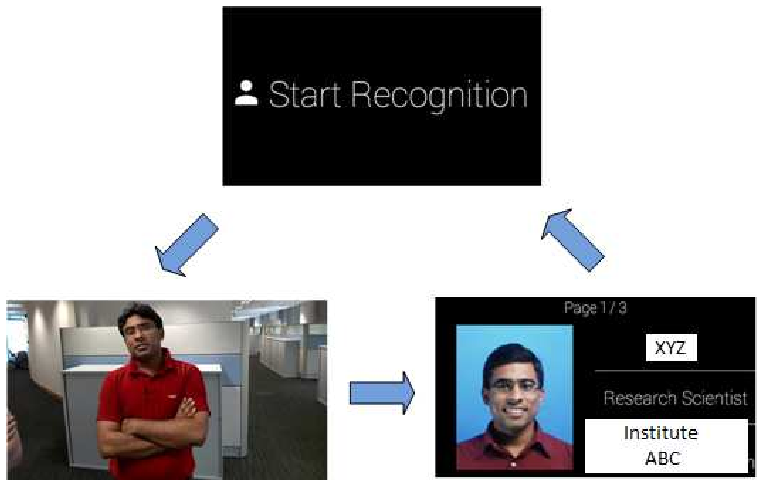

Fig. 3. Face recognition process flow in Google Glass (best viewed in zoomed version).

During test, the guided viewfinder will guide the user to capture a good face image of the targeted person. Once a face image is captured resulting in a successful face recognition, related information is displayed on the screen of GG. The displayed personal information include name, job title, company and portrait of the recognized person in the first page. Information on education, age, hobby, city, and food are displayed in second and third pages of the GG screen.

2.5 Implementation

GG runs on a dual core System on Chip (SoC) with 1GB RAM. The image captured by GG camera has resolution of 640×360 pixels. To investigate the tradeoff between computational complexity and privacy protection level, we designed and implemented two types of architectures for the system:

1. Local architecture solely on GG and
2. Client-Server (CS) architecture via Bluetooth to connect GG and a smartphone.

For the *Local architecture* GG, the whole process runs entirely on GG as a standalone system. The images captured using GG camera are processed directly on GG CPU and recognition results are shown on GG screen. For the *Client-Server architecture* (CS), GG serves as the client in charge of image acquisition and result display, and a smartphone serves as a server performing face recognition. Images captured on GG are compressed to 95% JPEG quality and cropped to 360×240 pixels before sending over to the smartphone. Upon receiving each image, the smartphone proceeds to perform face recognition. Recognition results are then sent back to GG. Finally, GG displays the results on its screen.

For coding development, we are using Eclipse IDE with Android Development Toolkit (ADT). The smartphone is HTC One M8. The target SDKs on Glass and smartphone are Glass Development Kit Preview (GDK) 4.4.2 and Android 4.4.2 respectively. Face recognition algorithms are written in native C/C++ codes and the Java/C++ interfacing is done via Java Native Interface (JNI). Android codes for the user-interface and Bluetooth communication are written in Java. OpenCV 2.4.8 is used for image capturing as well as processing.

3 System Evaluation

In this section, we present experimental evaluations on eye localization, recognition and computational costs for wearable FR on FPV videos from Google Glass.

3.1 Eye Localization

To be adaptive to head pose and lighting changes in FPV videos for eye localization, two eye detectors are employed in this system. The two detectors perform differently for front-view and oblique-view faces. The benefit of integration is also evaluated.

From FPV videos captured using GG, we randomly select 2675 detected faces. Among them, we further randomly select 100 frontal faces and 118 non-frontal faces. Both the sets have large changes in scales (near and far away faces). We perform the eye detection study using three methodologies: OpenCV, ISG and Fusion. For all the cases, if both eyes are successfully detected then it is considered to be a success, otherwise it is a failure. In our evaluation, it is found out that for both frontal and non-frontal views, the two eye detectors perform complementary roles. So a fusion of these two detectors gave us an improved eye detection results in FPV videos. As shown in Fig. 4, our Fusion system achieves over 90% accurate rate for frontal view cases and over 70% accurate rate for non-frontal view cases. This significantly increases the chance to recognize a person using GG before initiating an social interaction engagement.

3.2 FPV Database Description

To evaluate the performance of face recognition on FPV images [40], we use the face images collected using two wearable devices: Google Glass and head mounted webcam connecting to a tablet. This database contains faces of persons observed from FPV in natural social interactions, where people are involved in group meetings, indoor social interactions, business networking and all other

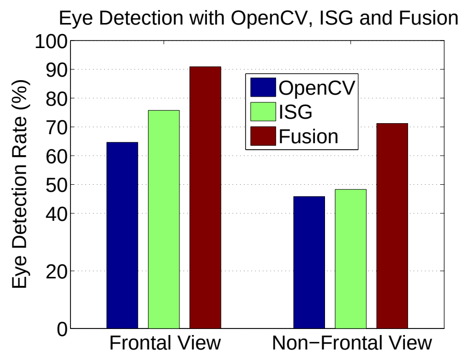

Fig. 4. Eye Detection Rate (%) using OpenCV, ISG and Fusion computed using Google Glass database (best viewed in color).

activities in indoor office environment. There are large changes in poses, expressions, illuminations and jitters because of head and/or camera movement. It is collected between Sep 2012 to Aug 2014 comprising of 7075 images of 88 people (average 80.4 images per person). Out of which 46 people are collected using Logitech C190 webcam and rest 42 people by using first version of the Google Glass [41]. The database is composed of 9 females and 79 males across 9 races. One sample image captured by GG and the extracted and normalized face images are shown in Fig. 5. The red box is shown in the face image where both the eye coordinates are successfully detected and blue box shows a face in which either one of the eye coordinates is not detected.

Fig. 5. Left, original image captured by Google Glass. Right, extracted normalized face images (red boxes: both eye coordinates are detected, blue box: either of the eyes is not detected). (Best viewed in color.)

3.3 Evaluation of Face Recognition on FPV Database

We evaluate the proposed face recognition algorithm WSSDA on the database built from FPV videos. We randomly select images of 42 people for training and images of the remaining 46 people are used for testing. We test the performance of face recognition for two application scenarios. In the first case, only one frontal view face image for each person is stored in the gallery database, rest all images in the probe database (termed as G1 for each of the compared methods in Fig. 6). This is similar to the commercial database of personal information containing only one mug shot image for each person. As mentioned previously and presented in the recent state-of-the-art wearable FR devices [1, 2], that keeping one mug shot image in the gallery may not be suitable for wearable FR for natural social interactions. However, in this work we perform experiments for such challenging scenarios.

In the second case, we select 7 images of different poses for each person and use them to form the gallery database and the remaining images are used as probe images (termed as G7 for each of the compared methods in Fig. 6). Two methods, *i.e.* LDA and PCA are selected as baseline methods for comparison as they are recommended for wearable FR in [1]. The comparison with previous method of eigenfeature regularization and extraction (ERE) on within-class subspace [22] is also performed.

Fig. 6 shows the plots of recognition rates (%) against the number of features used in the matching for two application scenarios: G1 (left) and G7 (right). It can be seen that the first scheme with only one mug shot image per person in the gallery database cannot generate satisfied result for wearable FR. In the second scheme, when using dimension of 100 features, the accuracy rate is close to 91%. For any kind of wearable device like GG, it is really very important to achieve good recognition rates while using small number of features. Evidently, a little more efforts would be required to build the gallery database as compared to the first simpler scheme in real-world applications.

3.4 Evaluations on Computational Efficiency and Battery Life

Computational Efficiency

The computational efficiency is crucial for real-time apps on GG and other mobile devices. If we run the whole FR process fully on GG, it turns hot in a short span of time (4-6 minutes, also depending on the number of recognitions performed) and the processing frame rate drops significantly. We performed an analysis of computational cost for FR on both GG alone and smartphone Client-Server via Bluetooth, and then, selected practical strategies of task arrangement for both the implementations.

The timings taken for FR on GG is shown in Fig. 7, left. The timings are taken for 100 successful recognitions performed consecutively. It can be seen that the timings are quite long and unstable when solely running on GG, however, on the Client-Server Bluetooth architecture, timings are shorter and much more stable as compared to GG, as shown in Fig. 7, right. The statistics and comparisons

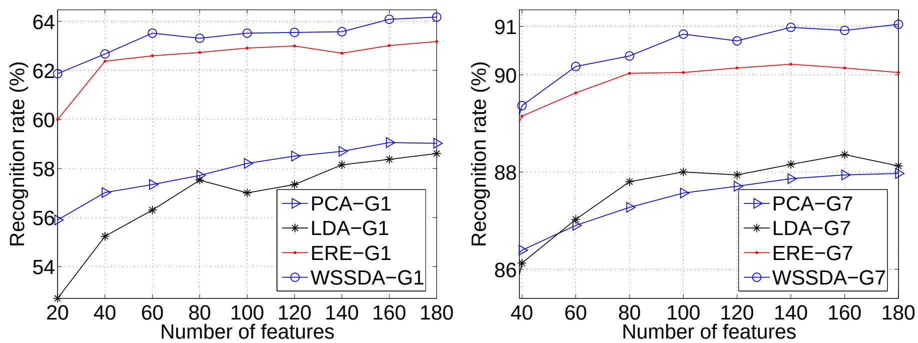

Fig. 6. Recognition rate vs Number of features used in the matching on wearable device database for two scenarios: Left (G1), 1 image per person in the gallery, rest all as probe images. Right (G7), 7 images per person in the gallery, rest all as probe images (best viewed in color).

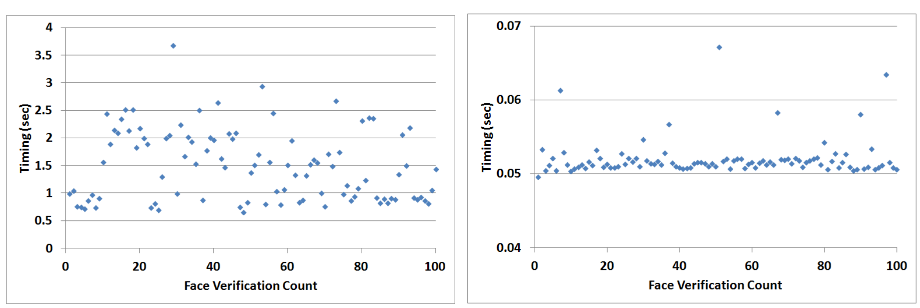

Fig. 7. Timings taken for 100 consecutive successful face recognitions on Google Glass (Left) and Smartphone (Right) with Client-Server Bluetooth architecture.

are shown in Table 1. The descriptions of the various timing breakdowns are as follows:

(a) Face Recognition refers to performance of the face recognition algorithm.
(b) Bluetooth Image Transmission refers to the timing needed to transfer the input image from GG to mobile device (not required for Local architecture).
(c) Total refers to the total round trip execution timing when GG acquires the input image till when the recognition result is achieved.

During our evaluation, we found that the Local architecture placed a huge strain on the Glass hardware, resulting in GG heating up quickly and performance degrades significantly. To minimize this heating effect, we stopped all recognition operations and allow GG to cool down for about 1 min, after each set of 10 recognitions.

Table 1. Performance comparison between the Local architecture and Client-server Bluetooth architecture for 100 successful recognitions.

	Local Architecture		Client-server Bluetooth	
	Average (sec)	Stand. Deviation	Average (sec)	Stand. Deviation
Face Recognition	1.4973	0.6409	0.0520	0.0025
Bluetooth Image Transmission	-	-	0.2808	0.0897
Total	1.4973	0.6409	0.3328	0.0922

From Fig. 7 and Table 1, it can be seen that the performance of the GG Client-Server architecture is much more consistent as compared to the Local GG architecture. The time fluctuations is mainly due to the heating up of the GG, when used as a standalone device. For Local mode, the time taken from capturing raw image to final recognition ID takes about 1.5 seconds, whereas for CS architecture, the total time taken is only 0.33 seconds. So our system can be applied as a real-time FR on the GG in real-world condition.

Battery Life

For battery life evaluation, we recorded the battery consumption for performing 100 consecutive recognitions on both Local and Client-Server architectures in Table 2. Both the GG and smartphone were unplugged and not connected to any power outlet.

From Table 2, it is evident that the battery life drops significantly when GG performs FR as a standalone device. However, the battery life drops only a little when FR is performed on smartphone operated in Client-Server Bluetooth mode.

Table 2. Battery life comparison between the Local architecture and Client-server Bluetooth architecture for 100 consecutive recognitions.

	% Battery Remaining		
Number of recognitions	Local (GG)	Client-Server Bluetooth	
		Google Glass	Mobile Device
0	100	100	100
10	92	97	100
20	87	94	100
30	80	91	100
40	74	88	99
50	67	85	99
60	60	82	99
70	52	79	99
80	45	76	98
90	39	73	98
100	33	70	97

4 Conclusions and Future work

In this paper, we have described a wearable FR system on GG for assisting people in social interactions. Our proposed system works in two modes of operations: local (standalone) and client-server Bluetooth (with a mobile phone) architectures. Numerous existing methodologies achieving high accuracy rates might not be suitable for wearable devices because of their limited hardware computing and power resources. We propose a system that includes multiple face and eye detections, regularized subspace based methods for training and testing of individuals in an unconstrained environment. Our system is able to achieve 91% accuracy rates with 7 face images in the gallery database. Out of the two modes of operations, local standalone system takes 1.4973 seconds for each recognition and client-server Bluetooth architecture takes only 0.3328 seconds, which is a real time implementation of FR on GG.

In future, we plan to improve the accuracy of FR, considering outdoor business meeting, social interactions and other group meeting scenarios. We intend to optimize our code and reduce the time taken for recognition in both local and client-server Bluetooth modes of operations. The optimization may also help in reducing of the build up of heat on GG, leading to better performance and usability for natural social interactions.

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