SMILE DETECTION USING MACHINE LANGUAGE

A MINI-PROJECT REPORT

Submitted by

CHETHAN CHOWDARY P (211519205030)

CHARLES J (211519205029)

GOKUL P (211519205050)

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BONAFIDE CERTIFICATE

Certified that this project report **"SMILE DETECTION USING MACHINE LANGUAGE"**is the bonafide work of **"CHETHAN CHOWDARY P (211516205030), CHARLES J (211516205029) and GOKUL P (211516205050)"** who carried out the mini-project work under my supervision.

SIGNATURE

Dr. KAVITHA SUBRAMANI M.E, Ph.D

HEAD OF THE DEPARTMENT,

Department of Information Technology,

Panimalar Institute of Technology,Poonamallee,

Chennai 600 123.

SIGNATURE

Dr.S.SUMA CHRISTAL MARY M.E, Ph.D

PROFESSOR,

Department of Information Technology,

Panimalar Institute of Technology, Poonamallee,

Chennai 600 123.

Certified that the candidates were examined in the university mini-project viva-voce held on______at Panimalar Institute of Technology, Chennai 600 123.

INTERNAL EXAMINER

EXTERNAL EXAMINER

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ABSTRACT

Smile or happiness is one of the most universal facial expressions in our daily life. Smile detection in the wild is an important and challenging problem, which has attracted a growing attention from affective computing community. In this paper, we present an efficient approach for smile detection in the wild with deep learning. Different from some previous work which extracted hand-crafted features from face images and trained a classifier to perform smile recognition in a two-step approach, deep learning can effectively combine feature learning and classification into a single model. In this study, we apply the deep convolutional network, a popular deep learning model, to handle this problem. We construct a deep convolutional network called Smile-CNN to perform feature learning and smile detection simultaneously. Experimental results demonstrate that although a deep learning model is generally developed for tackling "big data," the model canalso effectively deal with "small data." We further investigate into the discriminative power of the learned features, which are taken from the neuron activations of the last hidden layer of our Smile-CNN. By using the learned features to train an SVM or AdaBoost classifier, we show that the learned features have impressive discriminative ability. Experiments conducted on the GENKI4K database demonstrate that our approach can achieve a promising performance in smile detection. Machine learning approaches have produced some of the highest reported performances for facial expression recognition. However, to date, nearly all automatic facial expression recognition research has focused on optimizing performance on a few databases that were collected under controlled lighting conditions on a relatively small number of subjects. This paper explores whether current machine learning methods can be used to develop an expression recognition system that operates reliably in more realistic conditions. We explore the necessary characteristics of the training data set, image registration, feature representation, and machine learning algorithms.

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LIST OF ABBREVITIONS

ABBREVAITION	EXPANSIONS
ML	MACHINE LEARNING
AI	ARTIFICIAL INTELLIGENCE
DL	DEEP LEARNING
DDL	DATA DEFINITION LANGUAGE

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW :

The detection of faces and the interpretation of facial expression under varying conditions is an everyday task for humans, which we fulfill without effort. The identity,age, gender as well as the emotional state can be seen from someone's face. The impression we get from a displayed expression will affect our interpretation of the spoken word and even our attitude towards the speaker himself. Humor and sympathy are just two examples for essential information's that are primarily communicated via facial expressions. Hence, they have a high importance for our daily life even though weoften are not aware of it. For computer based systems on the other side, it still is hard toopen up this very important channel of communication. The rapidly expanding researchin face processing is based on the premise that information about a user's identity, state,and intent can be extracted from images, and that computers can then react accordingly,i.e., by observing a person's facial expression. Facial expressions are a form of nonverbal communication. They are a primary means of conveying social information among humans.

The task of automatic facial expression analysis can be divided into three main steps: face detection, facial feature extraction and classification into expressions. Face recognition process is influenced by several factors such as shape, reflectance, pose, occlusion and illumination . The face is a highly deformable object, and facial expressions come in a wide variety of possible configurations. Time-varying changes include growth and removal of facial hair, wrinkles and sagging of the skin caused by aging and change in skin color because of exposure to sunlight.

1.2 PROBLEM DEFINITION

In this project, we will be building a complete end-to-end application that can detect smiles in a video stream in real-time using machine learning along with traditional computer vision techniques. To accomplish this task, we'll be training the Let Net architecture on a dataset of images that contain faces of people who are smiling and not smiling. Once our network is trained, we'll create a separate Python script — this one will detect faces inimages via OpenCV's built-in Haar cascade face detector, extract the face region of interest (ROI) from the image, and then pass the ROI through LeNet for smiledetection.

When developing real-world applications for image classification, you'll often have to mix traditional computer vision and image processing techniques with machine learning.

1.3 SCOPE

These are the cascades for the face, eyes, and smiles. We must have each one of these features if our image is of a happy face. Obtain the code from each of these links, place it into a text editor and save your files according to the names mentioned above. Put all three XML files into the same folder where you will start a python notebook.

The only library you need to import is OpenCV. Even though it is a very powerful object-recognition tool, it is not the most powerful one. There are newer better ones out there, but OpenCV still delivers a lot of value and is a good way to understand the basics of object recognition.

After importing OpenCV (cv2), I called each of the cascades that were downloaded. For this, I just need to use the OpenCV function called Cascade Classifier.

CHAPTER 2

DATA SET COLLECTION

2.1 DATA SET DESCRIPTION

Crucial to our study was the collection of a database of face images that closely resembled the operating conditions of our target application: a smile detector embedded in digital cameras. The database had to span a wide range of imaging conditions, both outdoors and indoors, as well as variability in age, gender, ethnicity, facial hair, and glasses. To this effect, we collected a dataset, which we named GENKI, that consists of 63,000 images, of approximately as many different human subjects, downloaded from publicly available Internet repositories of personal web pages.

The photographs were taken not by laboratory scientists, but by ordinary people all over the world taking photographs of each other for their own purposes – just as in the target smile shutter application. The pose range (yaw, pitch, and roll parameters of the head) of most images was within approximately $\pm 20^{\circ}$ of frontal. This was done using two categories, which were named “smiling”, “not smiling” for the presence of prototypical smiles. This was done using three categories, which were named "happy," "not happy," and "unclear." Approximately 45 percent of GENKI images were labeled as "happy," 29percent as "unclear," and 26 percent as "not happy." For comparison we also employed a widely used dataset of facial expressions, the DFAT dataset.

Table 1. Statistical analysis of various data sets using the AdaboostM1 classifier.

Data Set	TP	TN	FP	FN	Accuracy	TPR	TNR	PPV	$F_{measure}$
CK+	2048.9	1916.59	33.1	33.1	98.35	0.98	0.98	0.98	0.98
CK+48	180.2	165.74	15.8	15.8	91.64	0.92	0.92	0.92	0.92
JAFFE	26.5	34.22	16.5	16.5	65.02	0.62	0.68	0.62	0.62

Table 2. Statistical analysis of various data sets using the Bagging classifier.

Data Set	TP	TN	FP	FN	Accuracy	TPR	TNR	PPV	$F_{measure}$
CK+	2049.2	1919.32	32.8	32.8	98.38	0.98	0.98	0.98	0.98
CK+48	179.8	165.66	16.2	16.2	91.44	0.92	0.91	0.92	0.98
JAFFE	27.3	34.47	15.7	15.7	66.62	0.65	0.69	0.63	0.64

Table 3. Statistical analysis of various data sets using the RUSBoost classifier.

Data Set	TP	TN	FP	FN	Accuracy	TPR	TNR	PPV	$F_{measure}$
CK+	2047.5	1919.19	34.5	34.5	98.29	0.98	0.98	0.98	0.98
CK+48	179.7	165.67	16.3	16.3	91.39	0.92	0.91	0.92	0.92
JAFFE	26.2	34.46	16.8	16.8	64.64	0.61	0.68	0.61	0.61

Table 4. Confusion matrix using the Bagging classifier for the CK+48 data set (20% of samples for testing).

Emotions	E1	E2	E3	E4	E5	E6	E7
E1	31	0	0	0	0	0	0
E2	2	5	0	0	0	0	0
E3	0	5	24	0	0	0	0
E4	0	0	5	16	0	0	0
E5	0	0	0	1	35	0	0
E6	0	0	0	0	3	13	0
E7	0	0	0	0	0	4	52

CHAPTER 3

SYSTEM ANALYSIS

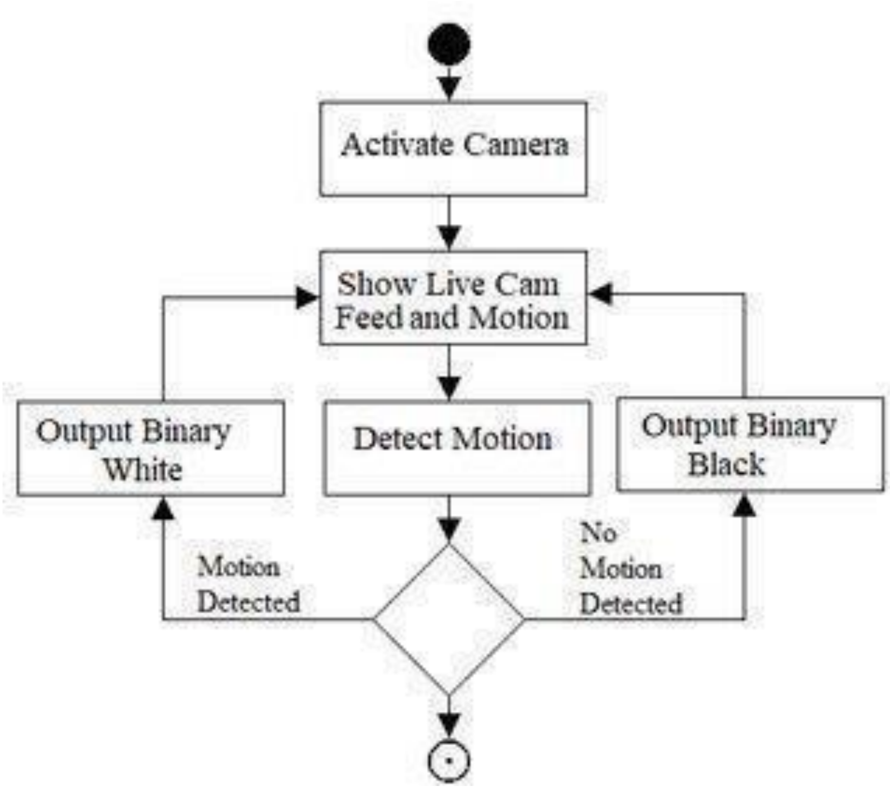
3.1 EXISTING SYSTEM

Existing system extracts features manually from an image needs strong knowledge of the subject as well as the domain. Otherwise, getting the complete information is not possible for doing the analysis. The number of trainable parameters increases drastically with an increase in the size of the image – Could not handle efficiently. Problem of overfitting and underfitting is occurred. Overfitting means, for the training data the model performance is very accurate andfor the testing data, the doesn't perform well. Underfitting means, both for the training data and testing data, model does not perform well.

3.2 PROPOSED SYSTEM

After extracting the intensity differences features of face images which are pre-processed by Histogram Equalization(HE). They run adaboost[7]–[10] to choose distinctive features and combined the selected weak classifiers as strong classifier. Trained over selected 500 features, Adaboost achieved the accuracy rate of 89.7 %. In the experiment each pixels weight is accumulated and the grayscale intensity of the picture was assigned proportional to the times of pixel used. The involved pixel where mainly distributed around mouth and few were from eye areas; considering that the main difference between smiling and non-smiling faces were in the lips, mouth and eye region. Smile involves many different pair of face muscles which can generate very wide variety of Smiles. In this paper Jacob Whitehill focuses on detection of prototypical smiles, commonly called as "Zygomatic Smiles"[11]. In this experiment testing and training datasets were DFAT and GENKI eyes were found automatically or manually. The tested image representation were Box Filters (BF),Gabor Energy Filters (GEF), Edge Orientation Histogram or a combination of BF and EOH. The tested learning algorithm were Gentle Boost and linear Support using Open CV Face Detector. Face- detection was then performed on the selected images in the Dataset. And then, a Half Octave Gaussian Pyramid was constructed over normalised imagette of the faces, which were of the size 64 X 64pixels

FLOW CHART :



CHAPTER 4

FACE DETECTION

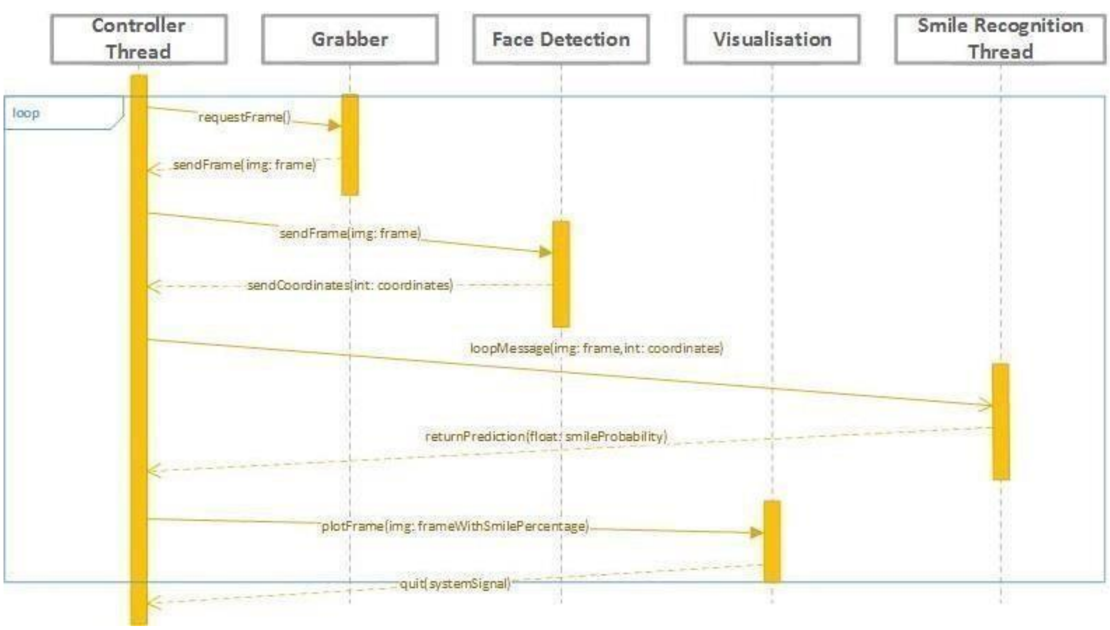
The face detection system used for this work (see [3]) integrates, among other queries,different classifiers based on the general object detection framework by Viola and Jones [4], skin color, multilevel tracking, etc .The Viola-Jones object detector is a cascade of classifiers. Each classifier uses a set of Haar-like features. The classifiersare ’weak’: each one has a very high detection ratio, with a small true reject ratio.

This way they act as a filter chain. Only those image regions that manage to pass through all the stages of the detector are considered as containing a face, see [5]. For a cascade of Kclassifiers, the resulting detection rate, D, and the false positive rate, F, of the cascade are given by the combination of each single stage, this framework allows a high image processing rate, due to the fact that background regions of the image are quickly discarded while spending more time on promising face-like regions. In order to further minimize the influence of false alarms, the facial feature detector capabilities were extended, locating not only faces but also eyes, nose and mouth.

This reduces the number of false alarms, for it is less probable that multiple detectors, i.e. face and its inner features, are activated simultaneously with a false alarm. Positive samples for the training sets of inner features were obtained by an-notating manually the eye, nose and the mouth locations in 7000 facial imagestaken randomly from the Internet. The images were later normalized by meansof eye information to 59×65 pixels. Five different detectors were computed:1-2)Left and right eye (18 ×12 pixels), 3) eye pair (22 ×5), 4) nose (22 ×15), and5)mouth (22 ×15). These detectors have been made publicly available, see .The facial element detection procedure is only applied in those areas which bear evidence of containing a face. This is true for regions in the current frame, where a face has been detected, or in areas with a detected face in the previous frame. For video stream processing, given the estimated area for each inner feature, candidatesare searched in those areas not only by means of Viola-Jones' based facial features detectors, but also by SSD-tracking previous facial elements. Once all the candidates have been obtained, a likelihood based on the normalized positions for nose and mouth is computed for each combination ,selecting the one with the highest likelihood.

Facial recognition uses computer-generated filters to transform face images into numerical expressions that can be compared to determine their similarity. These filters are usually generated by using deep "learning," which uses artificial neural networks to process data.

The OpenCV method is a common method in face detection. It firstly extracts the feature images into a large sample set by extracting the face Haar features in the image and then uses the AdaBoost algorithm as the face detector.



CHAPTER 5

SMILE DETECTION

The new Sony Cybershot DSC T-200 digital camera has an ingenious smile shutter" mode. Using proprietary algorithms, the camera automatically detects the smiling face and closes the shutter. To detect the different degrees of smiles by the subject, smile detection sensitivity can be set to high, medium or low. Some reviews argue that: "the technology is not still so much sensitive that it can capture minor facial changes. Your facialexpression has to change considerably for the camera to realize that"[8], or "The camera's smile detection – which is one of its more novel features – is reported to be inaccurate and touchy"[9].Whatever the case, detection rates or details of the algorithm are not available, and so it is difficult to compare the system. Canon also has a similar smile detection system. Sensing component company Omron has recently developed a "smile measurement software", which measures the amount of happiness that human subject of a photo are exhibiting [10]. The software uses a proprietary 3D model fitting technique to detect and analyze faces. This smile checking software rates how much a subject is smiling and gives a 'smile factor' on a scale of 0 to 100% Smile Detection for User Interfaces 605

This analysis only takes about 44 milliseconds using a PIV at 3.2Ghz and can be performed on images of faces as small as 60 pixels wide. Omron claims that this device is more than 90% accurate.

On a more scientific level, there are a significant number of papers that have tackled facial expression recognition, see the surveys .

Few Systems how ever, have been specifically designed for smile detection. The smile detector of used a vector of lip measures (extracted from an edge image) and a perceptron classifier. Edge features, however, may no be robust enough for practical use.

More elaborated is the method of , which used HLAC (Higher-order Lo-cal Autocorrelation) along with Fisher weight maps, achieving recognition rates of 97.9%. The BROAFERENCE system was developed to assess TV or multi- media content through smile measurement [15]. In this case, 8 mouth points are tracked, feeding a neural network classifier with the 16 feature vector. Unfortu- nately the authors do not give precise figures for its performance, although they claim that it achieves a 90% detection rate

The smile detection system proposed in this paper is based on a Viola-Jones cascade classifier. Training was carried out using 2436 positive images and 3376 negative images. The images were first extracted from Internet, then detected

and normalized by the face detection system described above. Figure 2 shows some examples of the positive images used for training.

When the cascade detector is searching over the image, it may produce mul- tiple positives around the positive region (the smile). Those detected rectangles largely overlap. Usually, isolated detections are false detections and they should be discarded. The number of neighbor detections is normally used as a confidence threshold.

For smile detection, the number of neighbor detections can also be considered as a confidence measure. The more neighbors detected around an image region, the more confidence that the region contains a smile. If the negative images of the training set contain mostly neutral faces then the number of neighbors can be considered as a measure of smile intensity. Figure 3 shows some of the faces used in the negative set.

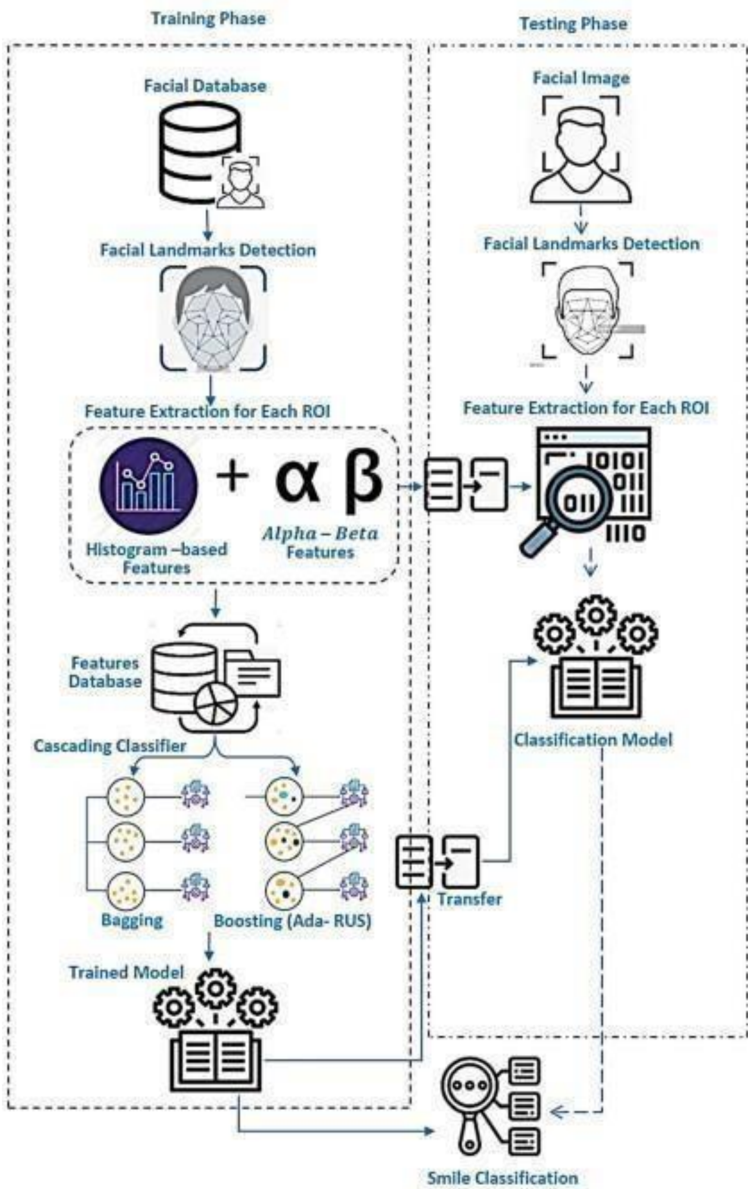
4 Experiments

4.1 Face Detection

The face detection system was tested with 74 video sequences corresponding to different individuals, cameras and environments, with a resolution of 320x240.

3. **Methodology**.

Face Detection The first step in the identification of a smile is to locate the face in the picture. For this function, the Viola–Jones method was used [41]. The face identified represents a Region of Interest (ROI) in the picture of a smile. The Viola–Jones method was also used to locate the eyes and mouth. The area of the eyebrow was determined from the position of the eye region. After the identification of facial regions, different techniques of image processing were used in each of the detected ROIs to remove the eyes and mouth. A search was then carried out on each of the extracted components to identify facial expressions



METHODOLOGY DIAGRAM

Negative images used for training the smile detector. They represent a single individual sat and speaking in front of the camera or moderating a TV news program. The face pose is mainly frontal, but it is not controlled, i.e. lateral views and occlusions due to arm movements are possible.The eyes are not always visible. The total set contains 26338 images.

In order to test the detectors performance, the sequences were manually an- notated, therefore the face containers are available for the whole set of images. However, eye locations are available only for a subset of 4059 images. The eyes location allows us to compute the actual distance between them, which will be referred below as EyeDist. This value will be used to estimate the goodness of eye detection. Mouth and nose detection were not analyzed.

Two different criteria have been defined to establish whether a detection is cor- rect:

a) Correct face criterium: A face is considered correctly detected, if the de- tected face overlaps at least 80% of the annotated area, and the area dierence is not doubled, and b) Correct eye criterium: The eyes of a face detected are consid-ered correctly detected if for both eyes the distance to manually marked eyes is lower than a threshold that depends on the actual distance between the eyes, EyeDist.

Table 1 shows the results obtained after processing the whole set of sequences with different detectors. The correct detection ratios (TD) are given consideringthe whole sequence, and the false detection ratios (FD) are related to the total number of detections. As for the face detector, it is observed that it performs more than twice faster than Viola-Jones' detector. Speed was the main goal in our application, the face detector is critical for the intended application.

MACHINE LEARNING:

Machine Learning has become one of the mainstays of information technology.

Machine learning can appear in many guises. We now discuss a number of applications, the types of data they deal with, and finally, we formalize the problems in a somewhat more stylized fashion. The latter is key if we want to avoid reinventing the wheel for every new application. Instead, much of the art of machine learning is to reduce a range of fairly disparate problems to a set of fairly narrow prototypes. Much of the science of machine learning is then to solve those problems and provide good guarantees for the solutions.

APPLICATIONS :

Product Recommends

Image Recognaigation

Automating employee access

controlBanking domain

Language translation

ADVANTAGES :

Handiling multiple data and multi variety data

Wide Applications

Scope of improvement

Smile Detection process

In order to test smile detection, experiments were carried out using a set of 4928 images of 108 individuals. The images were previously processed by the

Table1.Results for face and eye detection processing using a PIV at 2.2Ghz.

Viola-Jones Face detector used here TD FD

TD FD

Faces97.69% 8.25% 99.92% 8.07%

Left Eye 0.0% - 91.83% 4.04%

Right Eye 0.0% - 92.48% 3.33%

Proc. time 117.5 msecs. 45.6 msecs. Smile

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Comparison of smile detectors

Parameter This Omron Shinohara

Training images 5812 ? 72 1800

Test images 4928 24 3-min video

Individuals (test set) 108 4 3

Detection rate 96.1% (with 16 stages) more than 90%? 97.5%

False acceptance 2.3% (with 16 stages) ? ? 18%

rate (FAR)

Recognition rate 98.3% ? 97.9% ?(over the two classes)

(at 16% FAR)

Processing 45.6ms 44ms on a PIV less than ?

time on a PIV at 2.2Ghz) + at 3.2Ghz 50ms on

per 0.36ms a P I V a t

image (on a Core2 Duo at 2.4Ghz) 1.8Ghz

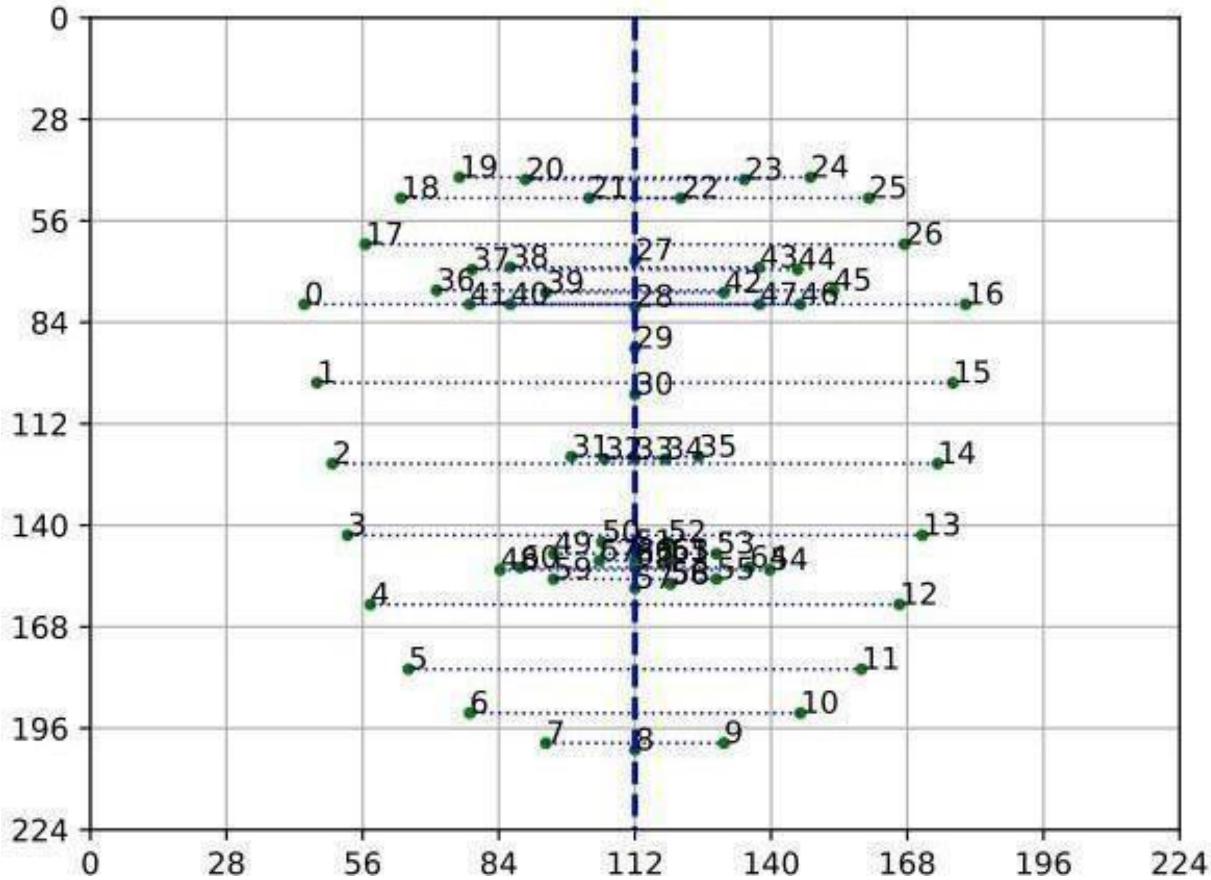
ROC curves for the smile detection system. With more than 16 stages the

detection rate may be considered too low to be useful, they were not shown in order to keep the Figure uncluttered.

Face detector. This particular set and the individuals were different from those used for training. Figure 4 shows the ROC curve for smile detection. Detection rates are above 96% with less than 3% false acceptance rate. This would compare well with Omron's system, of which we only know that is more than 90% accurate. On the other hand, the smile detector spends on average 0.36ms per (normalized) face image (runningon a Core CPU at 2.4Ghz, using a 16 stage classifier). This means that the total (face detection+smile detection) processing time per image is roughly 46ms.

The ability to estimate smile intensity was also put to test. In this case, a different dataset was used. In the already mentioned DaFEx database 8 professional actors showed 7 expressions (6 basic facial expressions + 1 neutral) on 3intensity levels (low, medium, high). The 'happy' pictures were extracted of thedatabase sequences , and the intensity level was compared with INTEGERS

FACE GRAPH :



Low, medium and high intensity happy expressions from DaFEx

Average number of neighbors obtained for the low, medium and high intensity smiles, over a total of 3440 images

Smile intensity	Number of neighbors Mean	Std. dev.
Low	7.63	5.31
Medium	11.31	8.01
High	18.40	10.09

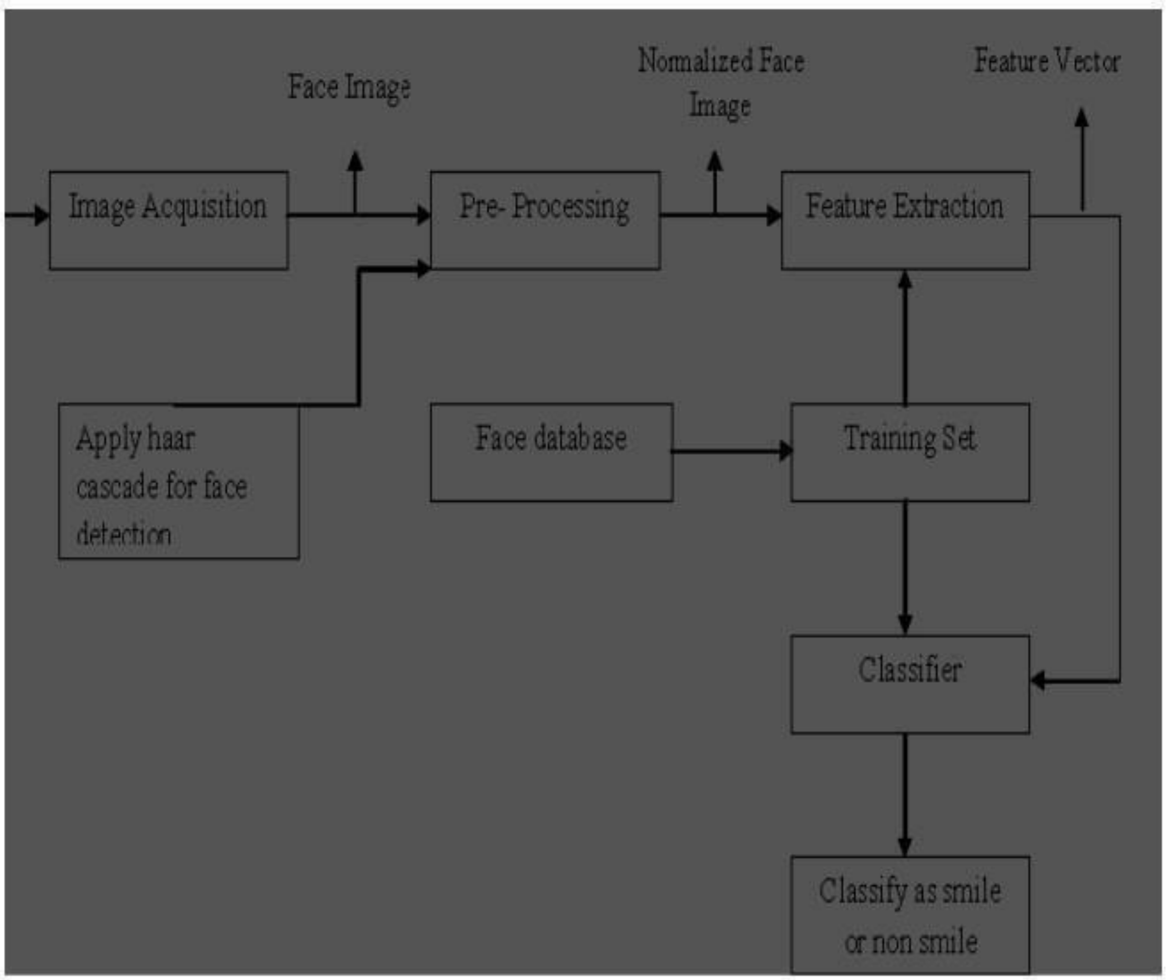
The number of neighbors given by the smile detection system. Table 3 shows the results. It can be seen from the table that smile intensity (as given by the database labels) and the number of neighbors are correlated.

Still, as the intensity discretization is sparse in the DaFEx database (i.e.only low, medium and high labels), a second database was tested. The Japanese Female Facial Expression (JAFFE) [17] database contains 213 images of 7 facial expressions (6 basic facial expressions + 1 neutral) posed by 10 Japanese female models. Each image had been rated on 6 emotion adjectives by 60 Japanese subjects (on 5-level scale, 5=high, 1=low).

This database allowed us to have numerical intensity values for the happy emotion

The correlation ratio between these values and the number of neighbors given by the smile detection system was 0.64 (95% confidence interval:[0.55, .., 0.71]). Again, this supports the fact that the number of neighbors is a good indicator of smile intensity.

SMILE DETECTION FLOWCHART :



Application: Instant Messaging Presence Control

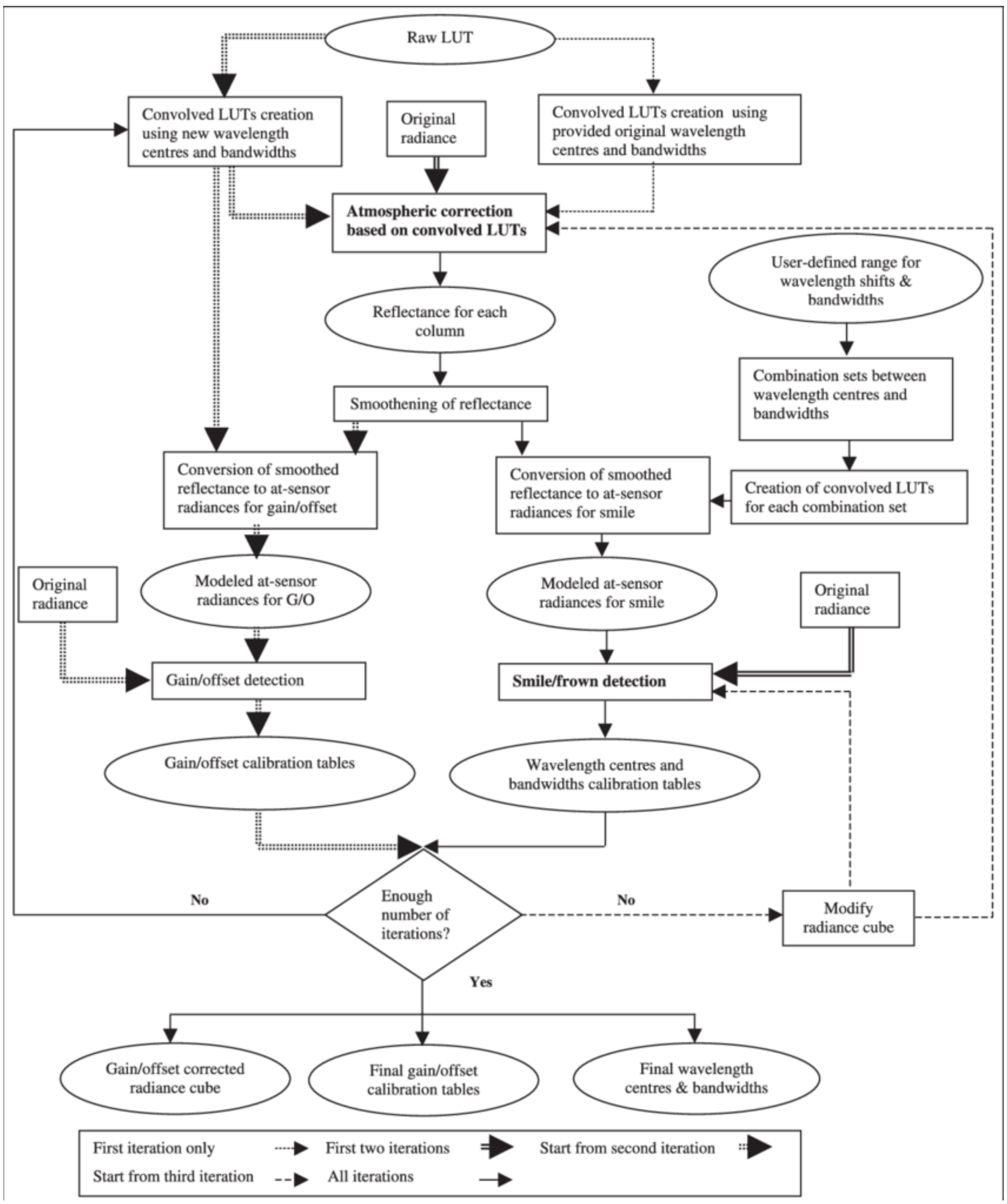
The face and smile detection systems described above were used in an application aiming at enhancing IM communication. The application uses a standard webcam to measure both presence (user status) and smile. In particular, it can control two features of the IM client: Away/online status and Smile emoticons. The application developed is able to detect when the user is in front of the laptop or away. The smile detector automatically inserts smile emoticons in theconversation window when the user is smiling. High intensity smiles can also bedetected, using the number of neighbors as a measure. The IM client applicationis controlled through keystrokes sent to its window (as specified by its title).

Keystrokes sent will not interfere with user's typing.

CHAPTER 6

EXPERIMENTS

SMILE DETECTION ARCHITECTURE:



Is a flowchart of the smile detection architecture under consideration. First the face and eyesare automatically located. The image is rotated, cropped, and scaled to ensure a constant location of the center of the eyes on the image plane. Next, the image is encoded as a vectorof real-valued numbers, which can be seen as the output of a bank of filters. The outputs of these filters are integrated by the classifier into a single real-valued number, which is then thresholded to classify the image as smiling or not smiling. Performance was measured in terms of area under

The ROC curve (A0),a bias-independent measure of sensitivity (unlike the “percent-correct” statistic). The A0 statistic has an intuitive interpretation as the probability of the system beingcorrect on a 2 Alternative Forced Choice Task (2AFC), i.e., a task in which the system is simultaneously presented with two images, one from each category of interest, and has to predict which image belongs to which category. In all cases, the A0 statistic was computed over a set of validation images not used during training. An upper bound on the uncertainty ofthe A0 statistic was obtained using the formula

Where np; nn are the number of positive and negative examples. Experiments were conducted to evaluate the effect of the following factors:

TRAINING SET :

We investigated two data sets of facial expressions: a) DFAT, representingdata sets collected in controlled imaging conditions, and b) GENKI, representing data collected from the Web. The DFAT data set contains 475 labeled video sequences of 97 human subjects posing prototypical expressions in laboratory conditions. The first and last frames from each video sequence were selected, which correspond to neutral expression and maximal expression intensity. In all, 949 video frames were selected. (One face could not be found by the automatic detector.) Using the Facial Action codes for each image, the faces were labeled as “smiling,” “nonsmiling,” or “unclear.”

Only the first two categories were used for training and testing. From GENKI, only images with expression labels of “happy” and “not happy” were included—20,000 images labeled as “unclear” were excluded. In addition, since GENKI contains a significant number of faces whose 3D

Pose is far from frontal, only faces successfully detected by the (approximately) frontal face detector (described below) were included (see Fig. 1). Over 25,000 face images of the original GENKI database remained. In summary, DFAT contains 101 smiles and 848 nonsmiles, and GENKI contains 17,822 smiles and 7,782 nonsmiles.

Training Set Size :

The effect of training set size was evaluated only on the GENKI data set.
First a validation set of 5,000 images from GENKI was randomly selected and subsets of different sizes were randomly selected for training from the remaining 20,000 images.

Embodiments provide techniques involving the detection of smiles from images. Such techniques may employ local-binary pattern (LBP) features and/or multi- layer perceptrons (MLP) based classifiers. Such techniques can be extensively used on various devices, including (but not limited to) camera phones, digital cameras, gaming devices, personal computing platforms, and other embedded camera devices. Embodiments, however, are not limited to such devices.

These techniques may advantageously consume a relatively small amount of resident memory (e.g., less than 400 KB),

Smile detection starts by finding the face location in the image. We rely on the classical, extremely fast Viola-Jones detector .

The deficiency in accuracy is compensated by the real time nature of the detector, and therefore a single missed detection is not essential among a stream of frames. On the other hand, at training time the execution speed is not critical,

and we use a more thorough face detector in order to take the most out of the annotated trainingdata. The discrepancy of using different methods at training and deployment does not pose aproblem, due to the alignment step that compensates for the different behavior of the two detection approaches.

This framework generally involves scanning images with one or more sliding-windows, and employs a boosting cascade classifier on Haar features todetermine whether there is a face or not. A Viola-Jones detector is provided in the publicly available OpenCV software package.

Reference throughout this specification to “one embodiment” or “an embodiment” means that a particular feature, structure, or characteristic described in connection with the embodiment is included in at least one embodiment. Thus, appearances of the phrases “in one embodiment” or “in an embodiment” in various places throughout this specification are not necessarily all referring to the same embodiment. Furthermore, the particular features, structures, or characteristics may be combined in any suitable manner in one or more embodiments.

Operations for the embodiments may be further described with reference to the following figures and accompanying examples. Some of the figures may include a logic flow. Although such figures presented herein may include a particular logic flow, it can be appreciated that the logic flow merely provides an example of howthe general functionality described herein can be implemented. Further, the given logic flow does not necessarily have to be executed in the order presented unless otherwise indicated. In addition, the given logic flow may be implemented by a hardware element, a software element executed by a processor, or any combinationthereof. The embodiments are not limited to this context.

illustrates an exemplary logic flow 100, which shows exemplary operationsinvolving smile detection. Although FIG. 1 shows particular sequences, other sequences may be employed. Moreover, the depicted operations may be performedin various parallel and/or sequential combinations.

Face detection is performed on the image at a block 104. From this, a face may be detected. Through such detection, the detected face may have a corresponding region (e.g., a rectangle region)

At a block 106, a facial landmark detection technique is performed to find multiple landmark points in the detected face's region. In embodiments, six landmark points (e.g., eye-corners and mouth-corners) may be employed for the detected rectangle region.

At a block 108, the face rectangle may be aligned and normalized according to the facial landmark points. Such alignment and normalization may be to a standard size (e.g., 60×60 pixels). However, other sizes may be employed.

Based on this, at a block 110, local-binary pattern (LBP) features are extracted from selected local regions of the normalized face image. In turn, each local regionis fed to a MLP (multi-layer perceptrons) based weak classifier for prediction at a block 112

At a block 114, outputs from the weak-classifiers of each local region are aggregated as a final smile score. This score may be in the range of 0˜1.0, where thelarger the score, the higher confidence of the detection.

At a block 114, outputs from the weak-classifiers of each local region are aggregated as a final smile score. This score may be in the range of 0˜1.0, where the larger the score, the higher confidence of the detection.

As described above, face detection may be performed at block 104 of FIG. 1. In embodiments, such face detection may follow the standard Viola-Jones boosting cascade framework. This framework generally involves scanning images with one or more sliding-windows, and employs a boosting cascade classifier on Haar features to determine whether there is a face or not.

At a block 114, outputs from the weak-classifiers of each local region are aggregated as a final smile score. This score may be in the range of 0˜1.0, where thelarger the score, the higher confidence of the detection.

As described above, face detection may be performed at block 104 of . 1. In embodiments, such face detection may follow the standard Viola-Jones boosting cascade framework.

Histogram of response of local binary patterns is usually used as texture descriptor ,and has demonstrated great success. illustrating how a basic LBP operator works. The standard LBP was later improved to reduce the pattern number. For instance, the basic LBP contains 256 patterns for 8-neighborhood.
However, the uniform LBP reduces 256 patterns into 59. Details regarding this are discussed in T. Ojala, M. Pietikainen, T. Maenpaa, Multiresolution gray-scale and rotation invariant texture classification with local binary patterns, IEEE Transactions on Pattern Analysis and Machine Intelligence, IEEE Volume 24.

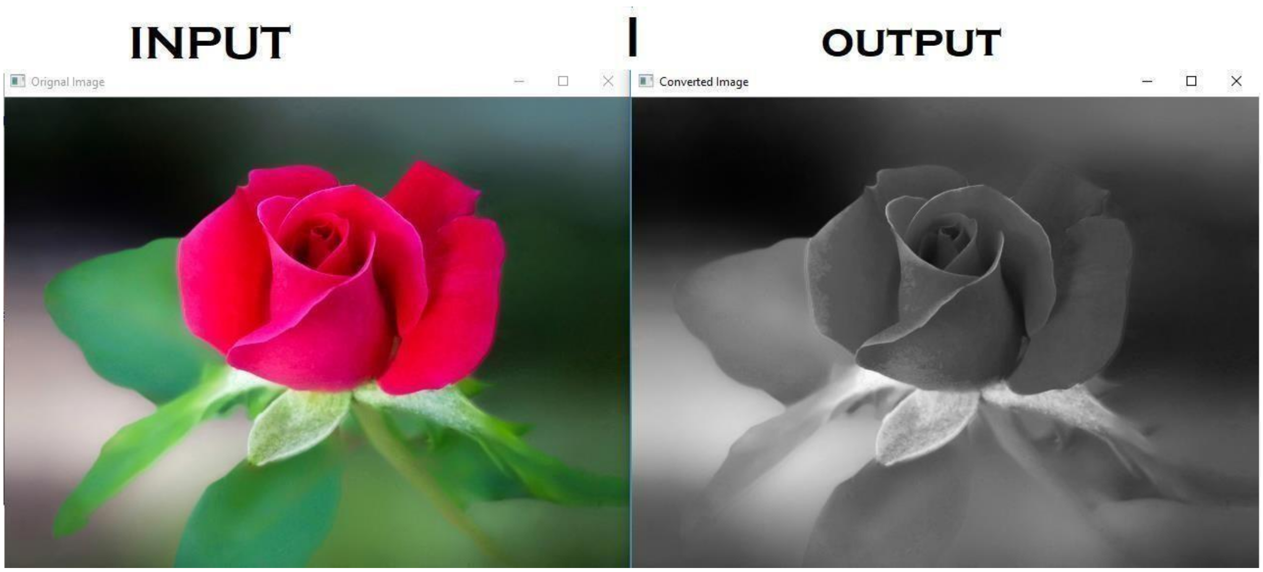
In embodiments, the local region is defined as (x, y, w, h) where (x,y) is the top- left corner point of the local-region, and (w,h) are the width and height of the local-region. It is evident that there are a lot of possible local regions with in the normalized faces. Embodiments may employ a training procedure in which a scalable window is slid over the face image (e.g., a 60×60 pixels image) to generate candidate local regions.
This training procedure make employ the following scheme:

Start with 15×15 window, step every 5 pixels in the face images;

Increase the window size by 5 pixel (such as from 15×15 to 20×20 window)The largest window is the face image size (e.g., 60×60

While testing, a face was considered as a successful detected only if the average deviation between the automatically detected eye allocation and true eye locations was less than the true intr-ocular distance.

IMAGE REGISTRATION :



For image registration they converted images to gray scale and then normalized the images byscaling the faces about eyes for reaching a Canonical face width of 24 pixels. • Keeping feature type constant BF + EOH classifier trained on DFAT had achieved only 87.5% accuracy on GENKI, whereas the classifier trained on equal sized subset of GENKI when use the database of images from the Web achieved an accuracy of 98.6% showing that web images database is more effective as web based data set are useful in capturing more wide range of imaging conditions however, they tend to lack in variability in facial expression.

Detection on the Data Set of GENKI-4K and fndsresult better than Gabor Energy Filters. In the experiment, they used 3577 out of 4000 images in GENKI4K Dataset. Images with ambigious cases having partiallightening on the faces and having serious illumination problem were removed from the Dataset.

CHAPTER 7

RESULTS AND DISCUSSIONS

7.1 DATA SET

There are various approaches available for smile detection technique. After going through several smile detection technique and amalgamating all those technique in the previous portion a generalized smile design of a face expression recognition system is implemented and constituted over techniques which is based on knowledge for section of facial expression recognition and Geometric Orientation technique. The reason for opting for this technique is that it does not have any reliability term issue and it could be applied in smooth manner. Fig 8 Face Recognition Approach A. Input Part: This is most important factor in Facial Expression Recognition. Image Acquisition operation is applied in thissection. The picture clicked is converted into digital form for the purpose of computation of image processing. After this, the acquired pictures are sent overto the Face Detection Algorithm. B. Face Detection Part: In this part, it executes theprocedure of discovering and implementing the method over a facial photo for FER. The facial picture is then segmented and analyzed with various geometrical orientation and hence, the face is verified. C. Geometric FeatureExtraction: In this part, The characteristic are taken from four most smile specific important fragmented key region i.e. lips, eyes, eyebrows and nose. These characteristics are then mined by proportion of 2D projection of segmented area. D. Output: After collecting all the characteristic the data is matched from various databases available such a GENKI4K and Adaboost databases and after configuring, it gives the output of whether is smiling or not. The problem associated with system of smile detection are identifying the face and natural facial expression and evaluating it. A lot of academic research have been done over FER (Facial Expression Recognition).

Compare the grey intensity pixel for obtaining distinctive feature from images. As multiclass and regression models gives better output as compared to binary based classifier Girard had proposed smile detection technique which is based on employed intensity-traind multi-class and regression model. Jain had used SVM and Multi-scale Gaussian Derivative (SVM)for smile detection obtaining an accuracy of 92.97 % over GENKI4K Database. H. Liu amalgamated SVM Classifier and Adaboost for smile detection and had obtained improved result over GENKI4K database[11]. Le An had used Holistic Flow- based face recognition method for extracting feature and Extreme Learning Machine (ELM) which had an accuracy of 88.3% on GENKI4K database and an accuracy of 94.4 % and mix database. Liu proposed and employed regression forest and conditional random forest for smile detection which had obtained and accuracy of 95.80% Labeled Faces in the Wild (LFW)which improves to

93.94 % on CCNV-Class database There are various approaches available for smile detection technique. After going through several smile detection technique and amalgamating all those technique in the previous portion a generalized smile design of a face expression recognition system is implemented and constituted over techniques which is based on knowledge for section of facial expression recognition and Geometric Orientation technique. The reason for opting for this technique is that it does not have any reliability term issue and it could be applied in smooth manner. Fig 8 Face Recognition Approach A. Input Part: This is most important factor in Facial Expression Recognition. Image Acquisition operation is applied in this section. The picture clicked is converted into digital form for the purpose of computation of image processing.

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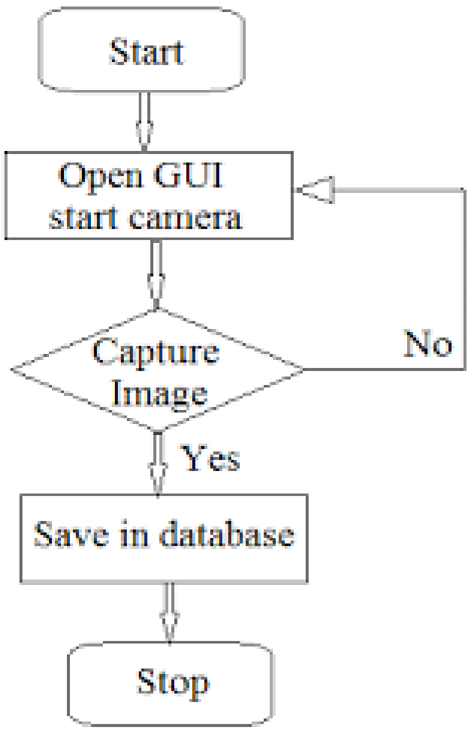
7.2 DESIGN OF A SMILE DETECTION:



Though, there is comparatively less research done for smile detection over Facial Expression Recognition, it is imperative that there should be improving accuracy with further research deepening. Geometrical Segmentation, Neural Network, LBP Feature Extraction and amalgamating SVM classifier and adaboost had enhanced the accuracy manifold over different databases like GENKI4K and CCNU-class database. However there are few challenges which would attractresearcher for more deeper studies. Low Detection Rate and high false alarm system, Detection over Oblique faces, posing facial expression picture taken in low visibility are some of the challenges which need to be eliminated for boosting the smile detection technique. Smile detection had attracted a lot of scholar in last decade, but now researcher are more focussed in detecting naturally occurring smile expressions. Differentiating and validating between fake and real smile is one of the most challenging task. Also it is very tough to detect People facial expression when they are using certain face cover like muffler and spectaclesetc.(as it will hinder face recognition). Also as per Sebe if a person already knowingabout the shooting of picture it is highly probable that they will intentionally smile which make it challenging for determining natural smile .After mitigating these challenge the major task is shooting with real appearance and in different type of exposure and impediment situation. Also, providing lable to available data set it challenge to overcome.

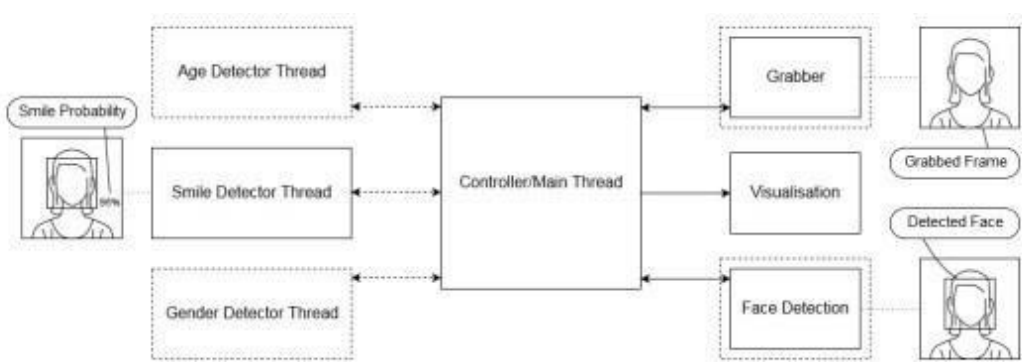
Collecting and labelling the un labled dataset is a stiff work and high Precision should be taken while labeling. Future expansion of research in this field will bring huge impact while collecting review from customer, the Speaker-Audience interaction and also in studying psychology and mental health of a person. This review paper represented a common available technique for smile detection. After reviewing various research paper the technique proposed in this review paper amalgamated different techniques available andprovide high accuracy in a faster manner. Content written in this paper will be proved beneficial for further Research and it could be further extended by matching with dataset of different data bases. There are various approaches available for smile detection technique. After going through several smile detection technique and amalgamating all those technique in the previous portion a generalized smile design of a face expression recognition system is implemented and constituted over techniques which is based on knowledge for section of facial expression recognition and Geometric Orientation technique. The reason for opting for this technique is that it does not have any reliability term issue and it could be applied in smooth manner. Fig 8 Face Recognition Approach A. Input Part: This is most important factor in Facial Expression Recognition. Image Acquisition operation is applied in this section.

Convert into digital form for the purpose of computation of image processing. After this, the acquired pictures are sent over to the Face Detection Algorithm. B. Face Detection Part: In this part, it executes the procedure of discovering and implementing the method over a facial photo for FER. The facial picture is then segmented and analyzed with various geometrical orientation and hence, the face is verified. C. Geometric Feature Extraction: In this part, The characteristic are taken from four most smile specific important fragmented key region i.e. lips, eyes, eyebrows and nose. These characteristics are then mined by proportion of 2D projection of segmented area. D. Output: After collecting all the characteristicthe data is matched from various databases available such a GENKI4K and Adaboost databases and after configuring, it gives the output of whether is smiling or not. The problem associated with system of smile detection are identifying the face and natural facial expression and evaluating it. A lot of academicresearch have been done over FER (Facial Expression Recognition). Still, smile detection is not so widely studied as it is very hard to catch subtle differences between different smiles as people may have different perception of smile and even one person may have different type of smiling expression. Many smile detection system have been developed in recent years with improving performances. C.Shan developed smile detection algorithm which is based on Adaboost, in which the algorithm compare the grey intensity pixel for obtaining distinctive feature from images. As multiclass and regression models gives better output as compared to binary based classifier Girard had proposed smile detection technique which is based on employed intensity-traind multi-class and regression model[13]. Jain had used SVM and Multi-scale Gaussian Derivative (SVM) for smile detection obtaining an accuracy of 92.97 % over GENKI4K Database. H. Liu amalgamated SVM Classifier and Adaboost for smile detection and had obtained improved result over GENKI4K database

It used Holistic Flow- based face recognition method for extracting feature and Extreme Learning Machine (ELM) which had an accuracy of 88.3% on GENKI4K database and an accuracy of 94.4 % and mix database. Liu proposed and employed regression forest and conditional random forest for smile detection. After finding all those major areas, the nostrils, eyes, lips and eyebrows region are then fragmented and characteristics are taken out from these key regions. These extracted features are then mined by taking the proportion of 2D Projection

SMILE DETECTION SOFTWARE ARCHITECTURE :

The target platform for our system implementation is NVidia Jetson TX2, a heterogeneous embedded platform with six ARM compatible CPU cores and an embedded GPU with 256 CUDA cores. For comparison, the experimental section will also benchmark the networks on a Desktop computer with and without a GPU. For implementing the smile detection system, asynchronous multithreading is used for parallelizing the computation. illustrates the software architecture of our system. The architecture consists of a main thread and worker threads, each dedicated to one task in the processing pipeline (grabbing, face detection, smile detection,



CHAPTER 8

CONCLUSION AND FUTURE ENHANCEMENT

Conclusions Perceptual User Interfaces aim at facilitating human-computer interaction with the aid of human-like abilities like computer vision, speech recognition, etc. In PUIs, the human face is a central element, since it conveys important information, particularly with respect to the user's mood or emotional state. This work proposes both a face detector and a smile detector for PUIs. Both can work together in real-time with modern commodity hardware. The face detector provides eye, mouth and nose locations in some situations, whereas the smile detector is able to give a smile intensity measure. Experiments confirmed that they are competitive with respect to extant detectors. These two detectorshave been used in an unobtrusive application that allows to control the user status of an Instant Messaging (IM) client. The application can also automatically insert smile/big smile emoticons in the IM client conversation window. As far as the authors know, it is the first time that such computer-vision-based aid is added to IM communication. Future work shall include the use of the smile detector in other applications that could take advantage of joy assessments: film previews, email clients, intelligent desktops, human-robot interaction, video games, wearable computing, etc. The natural extension would be to use the same methods described here to build a general facial expression recognizer which can give intensity values.

Another aspect for future work is the effect of other parts of the face other than the mouth. Smiles can involve subtle cheek raising around the eyes (the so- called Du chenne smile). However, this may not be a reliable cue, not least because itdoes not appear in every smile.

Emotion detectors are used in many industries, one being the media industry where it is important for the companies to determine the public reaction to their products. In this article, we are going to build a smile detector using OpenCV which takes in live feed from webcam. The smile/happiness detector that we are going to implement would be a raw one, there exist many better ways to implement it.

Step # 1: First of all, we need to import the OpenCV library.

```
import cv2
```

Step #2: Include the desired haar-cascades.

Haar-cascades are classifiers that are used to detect features (of face in this case) by superimposing predefined patterns over face segments and are used as XML files. In our model, we shall use face, eye and smile haar-cascades, which after downloading need to be placed in the working directory.

All the required Haar-cascades can be found here.

face_cascade = cv2.CascadeClassifier(cv2.data.haarcascades +'haarcascade_frontalface_default.xml')

eye_cascade = cv2.CascadeClassifier(cv2.data.haarcascades +'haarcascade_eye.xml')

smile_cascade = cv2.CascadeClassifier(cv2.data.haarcascades +'haarcascade_smile.xml')

Step #3:

In this step, we are going to build main function which would be performing the smile detection.

The live feed coming from the webcam/video device is processed frame by frame. We process the gray scale image, as haar-cascades work better on them.

To detect the face, we use:

faces = face_cascade.detectMultiScale(gray, 1.3, 5)

where 1.3 is the scaling factor, and 5 is the number of nearest neighbors. We can adjust these factors as per our convenience/results to improve our detector.

Now for each subsequent face detected, we need to check for smiles.

```
def detect(gray, frame):

faces = face_cascade.detectMultiScale(gray, 1.3, 5)

for (x, y, w, h) in faces:

cv2.rectangle(frame, (x, y), ((x + w), (y + h)), (255, 0, 0), 2)

roi_gray = gray[y:y + h, x:x + w]
```

```
 roi_color = frame[y:y + h, x:x + w]

smiles = smile_cascade.detectMultiScale(roi_gray, 1.8, 20)

for (sx, sy, sw, sh) in smiles:

cv2.rectangle(roi_color, (sx, sy), ((sx + sw), (sy + sh)), (0, 0, 255), 2)

return frame
```

Explanations –

The face data is stored as tuples of coordinates. Here, x and y define the coordinate of the upper-left corner of the face frame, w and h define the width and height of the frame.

The cv2.rectangle function takes in the arguments frame, upper-left coordinates of the face, lower right coordinates, the RGB code for the rectangle (that would contain within it the detected face) and the thickness of the rectangle.

The roi_gray defines the region of interest of the face and roi_color does the same for the original frame.

In line 7, we apply smile detection using the cascade.

Step #4:

We define main function in this step. After execution, the function can be terminated by pressing the “q” key.

```
video_capture = cv2.VideoCapture(0)

while video_capture.isOpened():

 # Captures video_capture frame by frame

 _, frame = video_capture.read()

gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)

   # calls the detect() function

canvas = detect(gray, frame)

 # Displays the result on camera feed

cv2.imshow('Video', canvas)
```

The control breaks once q key is pressed

if cv2.waitKey(1) & 0xff == ord('q'):

break

Release the capture once all the processing is done.

video_capture.release()

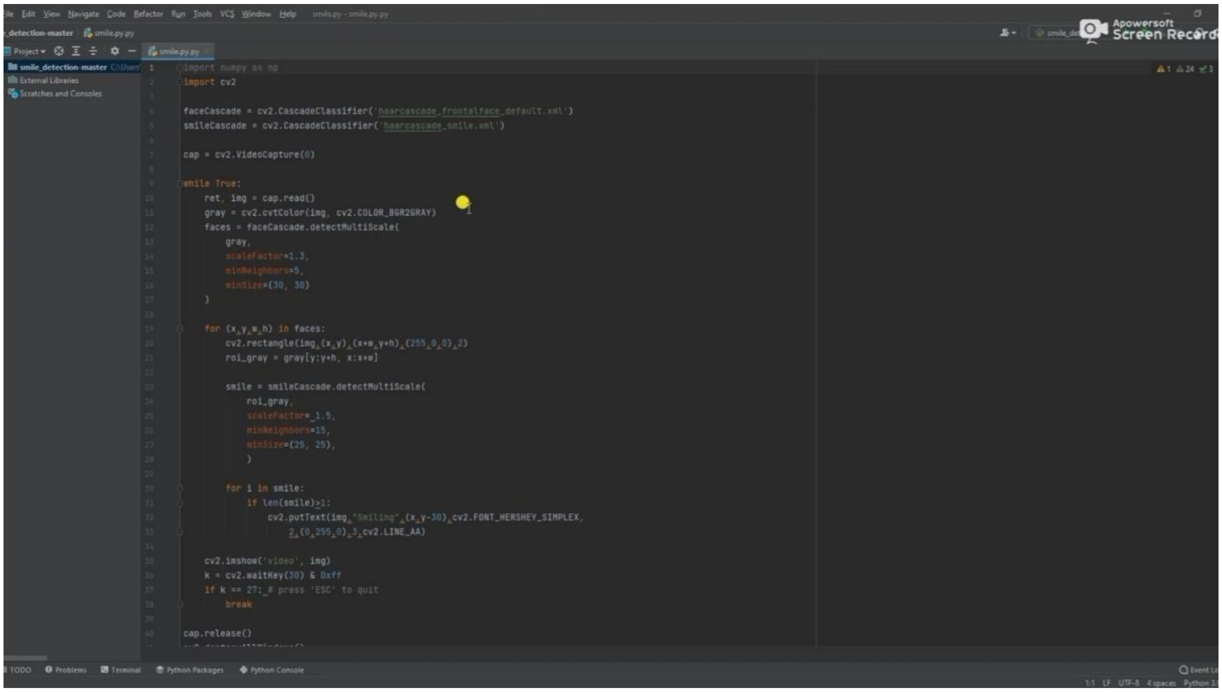
cv2.destroyAllWindows()

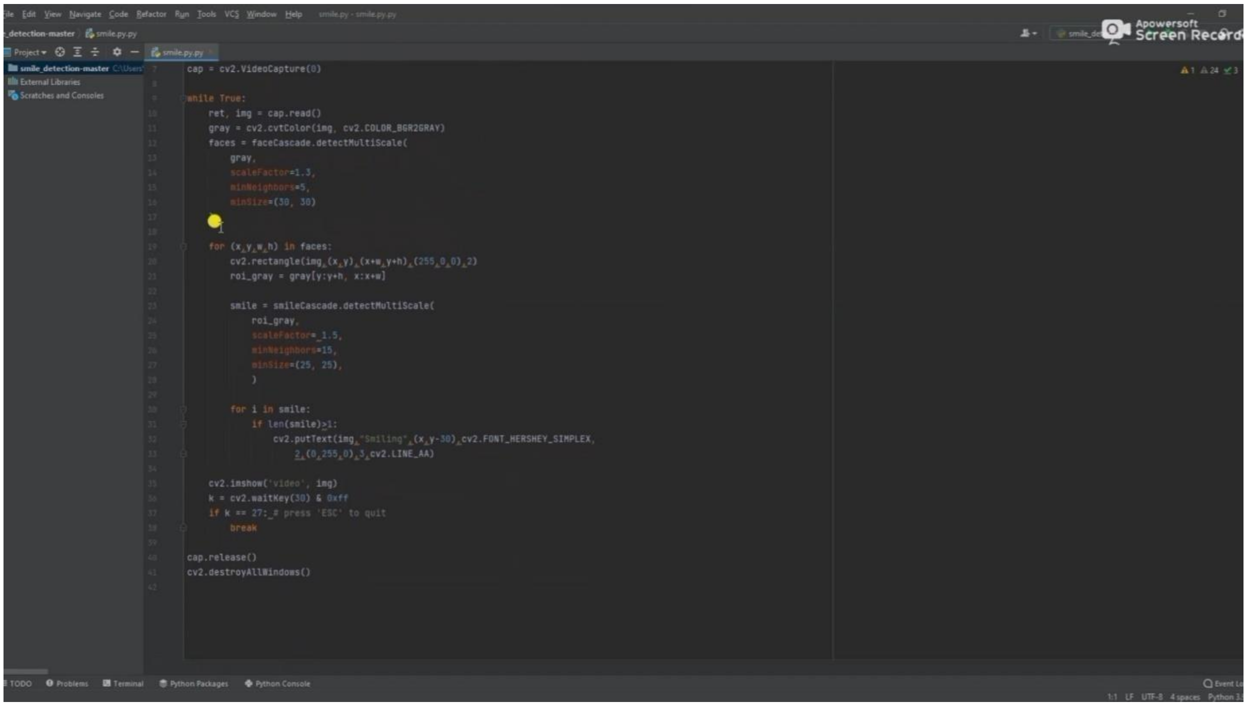
SAMPLE PROGRAM :

```
def detect(gray, frame):
    faces = face_cascade.detectMultiScale(gray, 1.3, 5)
    for (x, y, w, h) in faces:
        cv2.rectangle(frame, (x, y), ((x + w), (y + h)), (255, 0, 0), 2)
        roi_gray = gray[y:y + h, x:x + w]
        roi_color = frame[y:y + h, x:x + w]
        smiles = smile_cascade.detectMultiScale(roi_gray, 1.8, 20)

        for (sx, sy, sw, sh) in smiles:
            cv2.rectangle(roi_color, (sx, sy), ((sx + sw), (sy + sh)), (0, 0, 255), 2)
    return frame
```

SMILE DETECTION PROGRAM





8.1 :SOURCE CODE FOR SMILE DETECTION :

```
import numpy as np
import cv2

faceCascade = cv2.CascadeClassifier('haarcascade_frontalface_default.xml')
smileCascade = cv2.CascadeClassifier('haarcascade_smile.xml')
 cap = cv2.VideoCapture(0)

while True:
    ret, img = cap.read()
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    faces = faceCascade.detectMultiScale(
        gray,
        scaleFactor=1.3,
        minNeighbors=5,
        minSize=(30, 30)
    )

    for (x,y,w,h) in faces:
        cv2.rectangle(img,(x,y),(x+w,y+h),(255,0,0),2)
        roi_gray = gray[y:y+h, x:x+w]

        smile = smileCascade.detectMultiScale(
            roi_gray,
            scaleFactor= 1.5,
            minNeighbors=15,
            minSize=(25, 25),
            )

        for i in smile:
            if len(smile)>1:
                cv2.putText(img,"Smiling",(x,y-30),cv2.FONT_HERSHEY_SIMPLEX,
                    2,(0,255,0),3,cv2.LINE_AA)

    cv2.imshow('video', img)
    k = cv2.waitKey(30) & 0xff
    if k == 27:
        break

cap.release()
cv2.destroyAllWindows()
```

CHAPTER 9
APPLICATION:INSTANT MESSAGING PRESENCE CONTROL

The face and smile detection systems described above were used in an application aiming at enhancing IM communication. The application uses a standard webcam to measure both presence (user status) and smile. In particular, it can control two features of the IM client: Away/online status and Smile emoticons. The application developed is able to detect when the user is in front of the laptop or away. The smiledetector automatically inserts smile emoticons in the conversation window when theuser is smiling. High intensity smiles can also be detected, using the number of neighbors as a measure. The IM client application is controlled through keystrokes sent to its window (as specified by its title) Control Keystroke strings, both of status change and of the emoticons to insert, can be adjusted by the user.

An example keystroke string is ” :-) ”, the typical smiley .Special keys can be inserted too, between ”¡” and ”¿”. For example, the string” ¡HOME¿ ¡HOME¿)¡HOME¿-¡HOME,END¿” would insert a smiley (plus a blank space) at the beginning of the current text line in the conversation window(the ¡HOME¿ key must be sent before each character because in IM clients the conversation window is continually placingthe cursor at the end of the line both of status change and of the emoticons to insert, can be adjusted by the user. An example keystroke string is ” :-) ”, the typical smiley.

Special keys can be inserted too, between ”¡” and ”¿”. For example, the string” ¡HOME¿ ¡HOME¿)¡HOME¿-¡HOME¿:¡END¿” would insert a smiley (plus ablank space) at the beginning of the current text line in the conversation window(the ¡HOME¿ key must be sent before each character because in IM clients the conversation window is continually placing the cursor at the end of the line)Status change can be typically achieved with strings such as ”¡ALT ¿ade” that navigate through the options of the main menu.

The options of the application include: IM application window title string, IM conversation window title string, Smile keystroke string, Big smile keystroke string(typically ”:- D”), Time between sending of smile keystroke strings (in seconds, 0to wait for a no- smile before sending a new smiley), Away keystroke string, On-line keystroke string,Time without face before sending an Away keystroke string(in seconds), Smile detections before a smile or big smile keystroke string is sent, Sensitivity (the smaller the more smile detections), Smile/Big smile threshold and Show/hide live video window(the video window is hidden by default).The application can be executed with the argument ’-s’, which makes it start automatically and remain minimized in the tray. This way it will run unobtrusively. In Figure 6 the live video window is shown, when working with Windows Live messenger.

CHAPTER 10

ANALYSIS PATTERNS FOR FACE SMILE AND BIOMETRIC USING PUI

We must switch to normal, automatic, responsive and unobtrusive interfaces to respond to a wider range of situations, positions, users and tastes. A latest MCI concentrate, (Perceptual User Interfaces PUIs), aims to make interactions among people and devices more like interactions through people and the environment. (El Haddad, 2016). This chapter talks about the changing PUI domain and concentrates on the segments of PUI Computer-based vision policies that view applicable user information visually Graphical user interfaces have been the main tool for human-computer interaction (GUIs). Computers were streamlined and simplified by the GUI-based interaction style, especially for business software requirements where computers have been used for particular tasks (P hung, 2017). However, as computation advances and computing become more ubiquitous, (GUIs) can't comfortably meet the diversity of experiences expected to meet the needs of your users. We need to switch to standard, automated, versatile and discreet interfaces to accommodate a greater range of situations, responsibilities, users and interests (Au, 2020). HCI's target is to make human-computer experiences more analogous to the way humans communicate for one another and with the world, called perceptual user interfaces (PUIs). This article describes the emerging PUI field and focused on three main (PUI) tasks: computer- based vision strategies to demonstrate consumer awareness (Song, 2018). There is no Moore law for user interfaces. Communication between humans and robots has not dramatically changed for nearly two decades. Most users may connect by sort, point, and click their computers. Most HCI work in previous decades has been built to make interactive user interface users to track and detect directly (Rizzo, 2016). These properties will provide consumer with a basic model about what commands and actions are possibly and what their effects may be; they enable users would be conscious of total and taking charge of interaction with software solutions.

Although these attempts were common, their WIMP (Windows, buttons, menu, pointer) paradigm was a reliable global system face, Obviously, this paradigm concentrate, (Perceptual User Interfaces PUIs), aims to make interactions among people and devices more like interactions through people and the environment. (El Haddad , 2016). This chapter talks about the changing PUI domain and concentrates on the segments of PUI Computer-based vision policies that view applicable user information visually Graphical user interfaces have been the main tool for human-computer interaction (GUIs). Computers were streamlined and simplified by the GUI-based interaction style, especially for business software requirements where computers have been used for particular tasks (P hung, 2017). However, as computation advances and computing become more ubiquitous, (GUIs) can't comfortably meet the diversity of experiences .expected to meet the needs of your users. concentrate, (Perceptual User Interfaces PUIs), aims to make interactions among people and devices more like interactions through people and the environment. (ElHaddad, 2016). This chapter talks about the changing PUI domain and concentrates on the segments of PUI Computer-based vision policies that view applicable user information visually Graphical user interfaces have been the main tool for human-computer interaction (GUIs).

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Communication between humans and robots has not dramatically changed for nearly two decades. Most users may connect by sort, point, and click their computers. Most HCI work in previous decades has been built to make interactive user interface usersto track and detect directly (Rizzo, 2016). These properties will provide consumer with a basic model about what commands and actions are possibly and what their effects may be; they enable users would be conscious of total and taking charge of interaction with software solutions.

Although these attempts were common, their WIMP (Windows, buttons, menu, pointer) paradigm was a reliable global system face, Obviously, this paradigm would not work into different machine shapes and uses in the future. Computersare becoming smaller and more common, and their encounters with our daily life is becoming much significant. Large displays are becoming more popular simultaneously, and we are beginning to see a convergence of computers and television. (El Haddad). It is very important to connect with technology in a more public and conjectural way in all situations. Shortly, the way most people interact with many computing facilities will not be as they display, select and type, though still beneficial for many computers' solutions (2019). What we need are networking approaches that are well matched to how humans use computers. It does not match anything from lightweight, portable.

Appliances to powerful machines installed into homes, factories and automobiles. Will the nature of such complex future HCI specifications exist? We assume that it exists and that it is based on the connection between the people and the natural universe. PUIs are defined by interaction techniques incorporating an awareness of human natural abilities (necessary to conduct a range, motor, mental and perceptual ability). Using the contexts in which individuals communicate verbally with each other and the environment, the consumer interface is more normal and compulsive. Sensors must be clear and passive with the software, and computers have to interpret appropriate humancommunication networks and produce a naturally known output. This will includetechnological integration at various levels, including speech and acoustic synthesis and generation, computer vision, graphic design, simulation, language interpretation, sensing and suggestions dependent on modelling, conversation and listening (De Oliveira, 2018; Oday A., 2017). The figure below illustrates how research in various fields requires PUI. Since the figure shows the transfer of information within a traditional machine form factor, PUI is also meant for new form factors. A perceptive user interface applies human

sensing skills to the device, such as reminding the computer of the user's vocabulary or the user's face, body, hands... Some interfaces use the input PC while communicating between people, and engines are used. Multimodal UI has strong links that underline human communication skills. Weuse different modalities that result in better contact as we engage in
face-to-face interaction.

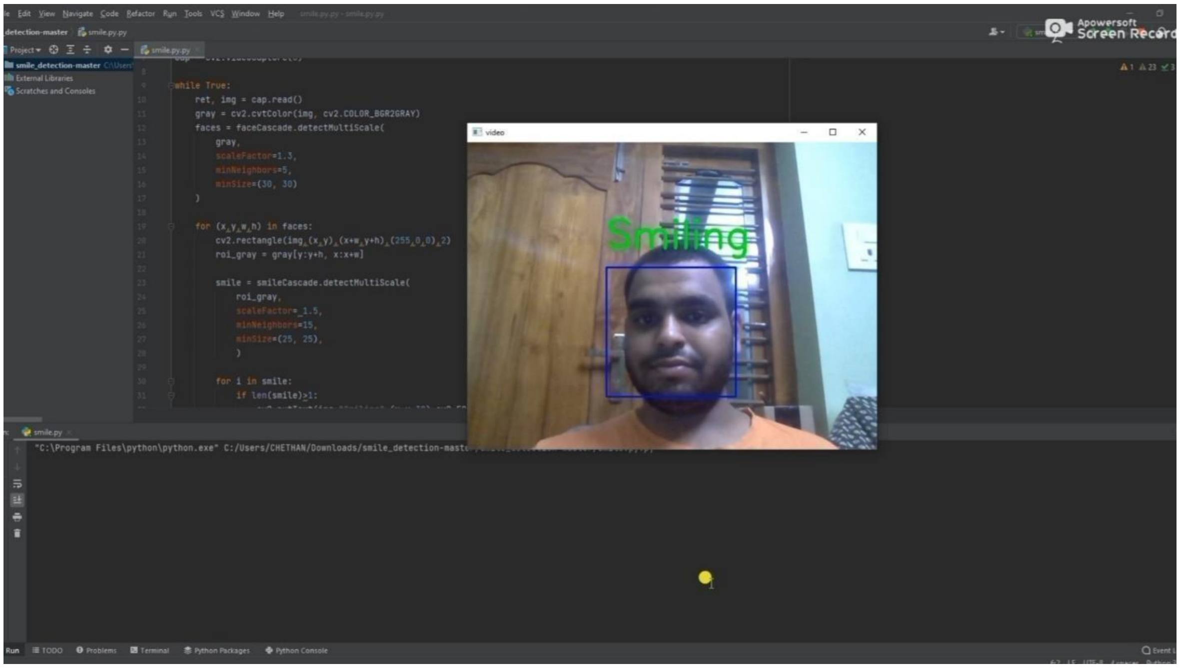
Much of the MUI function concentrated on device inputs(for instance, by speaking with pen-based gestures). The multimodal performance uses multiple ways to interpret what is viewed by individuals using auditory, cognitive, and communication abilities, including visual presentation, audio,and tactile feelings. In multimodal user interfaces, various modalities are sometimes used separately or even concurrently or closely related. (Oday A., 2017; Ryu, 2017). Multimedia UI, that has undergone tremendous study throughout the past two decades, utilizes perceptual abilities to understand the user's details. Normal media is text, graphics, audio or video. Multimedia studyfocuses on media, multimodal study on human sensory sources.

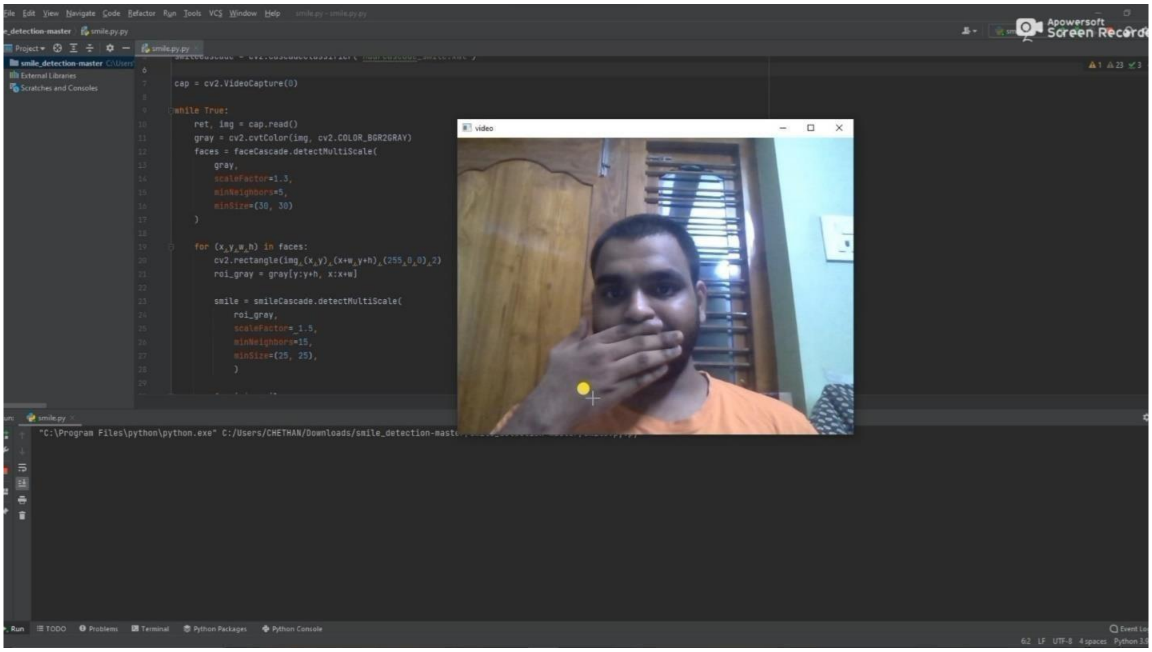
Multimedia review is a multimodal branch of output testing from that angle. PUI incorporates perceptive, multi - modal, with multimedia interfaces to bear on developing more natural, responsive interfaces. PUIs can improve the usage of machines as instruments or equipment, improving GUI-based software explicitly, for example, through taking into account motions, voice, and eye gaze('No, that'). Maybe more significantly, these emerging developments would allow computers to be widely used as assistants or agents who communicate in more humane ways. Perceptual interfaces would enable various input modes, including such speech alone, speech and motion, text and contact, vision and synthetic voice, any of which could be suitable in different situations, be it web applications, advocates sensory intelligence as essential to interfacing with potential generations of machines; it identifies two classes of responsive sensor-based environments and technology expected to help them. latest investigation about computer-based sensing and interpretation of human behavior in particular vision areas. They offer a wide view of the field and explain two initiatives that, using visual experiences, improve graphical interfaces.Reeves and Nass discuss the criteria for a deeper understanding of human cognition and psychological in conjunction with technology interaction, and their studies concentrate on human beings.

Additional knowledge on unique Perceptual User Interface domains, that is haptic and computational effects (Hassena, 2019).Channel based Face Analytics.A device able to recognize or verify an individual from a digital picture or video source is a technology. Many processes function, however overall, by comparing a specified image's chosen facial features with faces in a database.

Different facial recognition technologies exist. The program, which can recognizean individual by analyzing patterns based on facial structure and form, is also identified as biometric artificial intelligence. In the past, it has seen broader applications of mobile platforms and other aspects of technology including robots, though initially a computer program. Currently used in access management authentication schemes, it can be contrasted with some other biometrics such as facial patterns system.

OUTPUT SCREENSHOTS :





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