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Design and Implementation of Deception Detection System Based on Reliable Facial Expression

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Abstract: Human face is a wealthy source of information which provides reliable cues to deception. The Deceptive Detection Systems (DDSs) through the identification of facial expression are non-invasive, mobile and cost effective. In this study, the DDS is designed depending on Facial Action Coding System (FACS) to extract the facial features. The main idea of this FACS is coded the facial muscles movements using Action Units (AUs). Each AU represented the movement of certain facial muscle. The proposed system discriminates lying subjects from the innocent one based on presence or absent the facial AUs. Eight AUs are used as potential indicators for deception that incorporated into a single facial behavior pattern vector. Database that used to validate the proposed system are collected from 43 subjects (20 males, 23 females) most of them between ages 18-25. The number of video clips that obtained from collected database after editing was 400 video clips. Virtual Generalizing Random Access Memory Weightless Neural Network (VG-RAM WNN) classifier is used to make decision in last stage of DDS. The proposed DDS was tested three times, accuracy 84, 85 and 90% of spotting liars are achieved when using both genders, only female and only male participants respectively. The VG-RAM classifier was built by FPGA Model using Xilinx system generator and implemented on Spartan-3A 700 A Kit.

Key words: Movement, facial muscle, database, video clips, spotting liars, validate

INTRODUCTION

Reliable DDS is a crucial challenge for researchers in various scientific fields. Detecting deceptive is important in various areas of life such as police realization, airport and homeland security, security agencies, law enforcement, counter-terrorism. The human's mood and notion can be read from his face based on the basic structure of the face, muscle tension and also the change in the conveying expressions of the face like smile, scowl, etc. (Owayjan *et al*., 2012). Researchers are presented many techniques and methods for detecting deceptive as individuals. Facial expressions are an important source that reveals the bad intentions of person and danger demeanor detection. Moreover, the facial video can be captured and analyzed without the participant's knowledge he is under the test by lie detector device this makes the subject fell comfortable during the interview in other words if the participant know that he was under the test this makes him confused and afraid during the interview and this potentially giving incorrect deceptive cues (George *et al*., 2017).

The main purpose of this study is to design and implement a DDS based on AUs recognition technology that defines by FACS developed by Ekman and Rosenberg (2005). This study is arranged as follows; related research is firstly rewired, followed by an explanation to the general DDSs, then, an overview of the proposed DDS with its stages, then, the simulation results followed by hardware implementation, finally, the conclusion.

Literature review: In recent years, the focus of DDSs has been on three kinds of indicators: temperature change in face area (Jain *et al*., 2012; Azar and Campisi, 2014), eye blink (George *et al*., 2017; Singh *et al*., 2015) and facial expressions (Owayjan *et al*., 2012; Su and Levine, 2014). All of these techniques used video datasets.

Jain *et al*. (2012), deception was detected based on thermal image of inner and outer edges of eyes, nostrils outer edge, nose tip and mouth outer edges. Their experiment includes sixteen participants. They achieve 83.5% accuracy to discriminate deceptive and honesty. The temperature change in the nose area was used for deceptive detection as proposed by Azar and Campisi

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(2014). Subtle change in temperature was recorded using special infrared camera. They analyzed this temperature change using two methods Time domain analysis and frequency domain analysis the accuracy was 69 and 84%, respectively.

The deceptive was detected based on eye blink as presented by Singh *et al*. (2015). They used special camera that capture 60 frames per second, then, they calculate eye blink in certain duration of time. Finally, they compare the result with threshold value (that calculated for each participant as individual during the interview) in order to determine whether it increased or decrease. Five subjects were participant in their research. The results were two of the participants were lying. The researchers by George *et al*. (2017) attempted to prove the theory of eye blink behavioral during lying. They used AU45 (Action Unit for eye blink) for calculate eye blink count and duration. The 50 subjects were participant in their research. The results show that blink count and blink duration were increase during lying for most of the participants.

DDS based on facial micro-expressions is presented by Owayjan *et al*. (2012) by using LabVIEW program. FACS was used for encoded the basic facial expression and emotion such as: joy, sadness, happiness, surprise, fear, disgust, contempt, anger each with its associate AUs of different muscles movements. The camera was capture 25 frame per sec while micro-expression takes 1/25 of a sec, if the camera capture 5 frame or less for the same expression at the same time considers as a micro-expression and that indicate that subject was lying. The accuracy was 85% where only 5 expressions from the nine basic facial expressions are depended as indicators for deceptive detection. The system tested by four subjects. Su and Levine (2014) lie was detected base on facial expressions. The proposed method was relying on four facial clues (eyebrow motion, mouth motion, eye-blink and wrinkle occurrence) to distinguish lie from honesty. Database were collected from YouTube of high-stakes deception videos of real-world situations, they obtained 324 video clips. The AUs that they depend on as facial expressions are AU1, AU2, AU4, AU12, AU15 and AU45 that used as potential indicators for spotting liars, this AUs were used to identify the fake and genuine expressions. The accuracy was 76.92%.

MATERIALS AND METHODS

General deceptive detection systems: The general block diagram of deceptive detection systems which used video datasets can be seen in Fig. 1. The system consists of three main stages which are video recording and data base collection, feature extraction and decision maker. First stage is video recording and datasets collection consists of collection of data that provides a platform to test deceptive detection systems. The second stage of the system is features extraction which represents the potential indictors to distinguish liars from truth-tellers. The last stage is decision maker that depend on extracted features to given the decision the subject was lying or tell the truth. All stages of the system will explain in details in this study.

Video recording and datasets collection: There are a few datasets is used by researcher in deception detection studies, none of these datasets that specifically includes facial expressions of people when telling lies have been made available to the public. In order to build DDS based on facial expression it's required to collect datasets, approximately each DDS has its own datasets which provide baseline to test the robustness of the system. In this research The databases are collected to check the validity of the facial cue could be adopted as reliable indicators for detecting deception as well as test the robustness of the algorithms that used in building the proposed DDS.

Feature extraction: Features extraction in DDS based on facial expression mean extract some facial clues to adopt it as reliable indicators to separate lairs from truth-tellers. There are many methods to extract the features from the human face, the most common and more general methods that used in independent systems are depend on FACS to extract the facial features such methods used in many DDSs (Owayjan *et al*., 2012; George *et al*., 2017; Su and Levine, 2014). The FACS define the facial behavioral using AUs which represent the facial muscles movement (Bartlett *et al*., 2000; Tian *et al*., 1999), this FACS depend on detecting these AUs. Each articulation of the face is identified by distinct AU number according to FACS (Ekman, 1993). A reliable and robust method to detecting

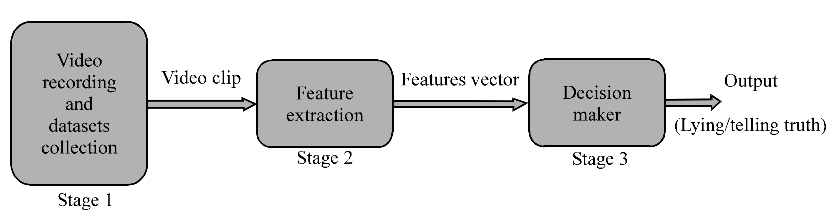

Fig. 1: General block diagram of deceptive detection systems that used video database

AUs is used two types of features as presented by Baltrusaitis *et al*. (2015), these two types of features are appearance features and geometry features. This AUs detection method includes many step and algorithm. The first step of this method is face detection, next step is facial landmark detection which necessary for facial feature tracking when using video database and for extracting represent geometry based feature. Then, face alignment and extract Histograms of Oriented Gradients (HOGs) that represent appearance features which extract as proposed by Felzenszwalb *et al*. (2010), last step of this AUs detection method is classification that given AUs state in a face image.

The most popular face detector to date is Viola-Jones face detector (Viola and Jones, 2004) that has ability to process images extremely quickly, detect face with different skin color and can detect face with eye glasses. This face detector used by many DDS that depend on facial clues.

The facial landmark was detected base on bounding box of the face that obtain from face detector. Facial landmark is important for tracking the face and to extract geometry based features. The Constrained Local Neural Field (CLNF) algorithm used for facial landmark detection and tracking as proposed by Baltrusaitis *et al*. (2013), this approach can detect and track facial landmarks in poor lighting conditions in the presence of occlusion and can detecting landmark for unseen datasets. The whole shape of this model can be described using four type of parameters p = (s, R, q, t) which are the scale factors, object Rotation R, 2D translation term t and non-rigid shape the described by q. The location of ith feature denoted as x_i which is controlled by these four parameters based on Point Distribution Model (PDM) that can be describe using the following Eq. 1:

$$x_i = s.\, R\, (\ddot{x}_i + \Phi_i q) + t \tag{1}$$

Where:

$X_i = (x_i, y_i)^T$ = The 2D location of ith feature
$\ddot{x}_i = (x_i, y_i, z_i)^T$ = The mean value of the ith feature
Φ_i = A 3×m principal component matrix

HOGs used to code the face image to extract the appearance features from it as proposed by Felzenszwalb *et al*. (2010). Classification is the last step of this AUs method that used the SVM classifier due to its high recognition rate that train on many publically available AUs detection datasets (Baltrusaitis *et al*., 2015). This automatic AUs detection method used in this research.

Decision maker: In DDSs the classification is tried to categorize the extracted features into two classes which are lie and true classes. The most common extracted features in DDS based on facial expressions is AUs which are binary type features as explained. Among several classifiers, VG-RAM WNN classifier is chosen due to this classier is design to handle binary patterns with high recognition rate, simplicity of hardware implementation and fast training and testing (De Souza *et al*., 2010). The VG-RAM will classify each unknown sample based on training samples that store in the RAM. This memory stores the input-output pairs of training samples, each sample with its output class store in the RAM during training phase. During testing phase, an associative search to the memory of VG-RAM is needed to calculate the hamming distances between the input sample which need to be classified and all training samples that stored in the memory. The class of the input unknown sample depends on minimum hamming distance. The output of each neuron in VG-RAM network is depend on the distance function given by VG-RAM nodes called hamming distance (De Souza *et al*., 2010) (Eq. 2):

$$d^{HD}(x, y) = \sum_{i=0}^{m-1} [z_{x,i} \neq z_{y,i}] \tag{2}$$

where, d^{HD} (x, y) which represents the hamming distance among two objects x and y and i represent the index of respective element called Z while m represents the total number of variables. In other words, hamming distance produces the number of difference between the variables paired by i. The generalization of this classifier has been ensured by store all address of training patterns and searching for the nearest class to the input pattern need to be classified. Figure 2 shows the block diagram for VG_RAM (De Souza *et al*., 2007, 2008).

Proposed deceptive detection system: The proposed DDS is depending on facial clues to detect deception it consists of three main stages the stages are: collect database, features extraction and AUs detection and the last stage classification. The layout of the proposed system and stages are show in Fig. 3. In order to extract all potential facial muscles movements, the camera was setup to face the subject's head. The interviews are recorded using Sony video camera for 43 participants during lie and truth responses, then, these obtained 43 videos are edited to prepare the database where 400 video clips are obtained after editing process this represent stage 1 of the proposed system. After that frame by frame is analysis for each video clip of collected database, the face of each participant is detected in order to extract features from it, the features are extracting from each individual frame in video clips. Facial landmark detection is used for tracking the face and extracting geometry based feature. The geometry and appearance features lead to detect AUs that represented facial muscles movements, these steps represent stage 2

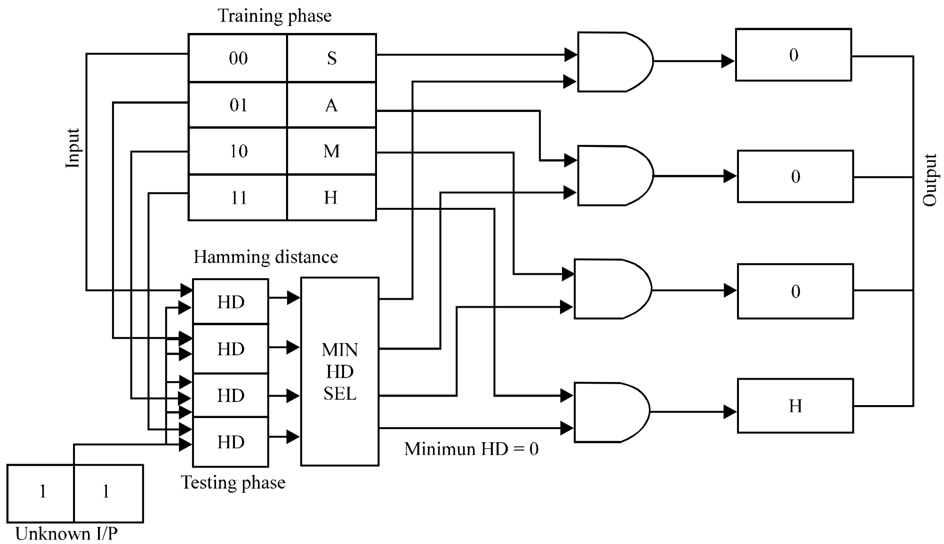

Fig. 2: Block diagram of VG-RAM

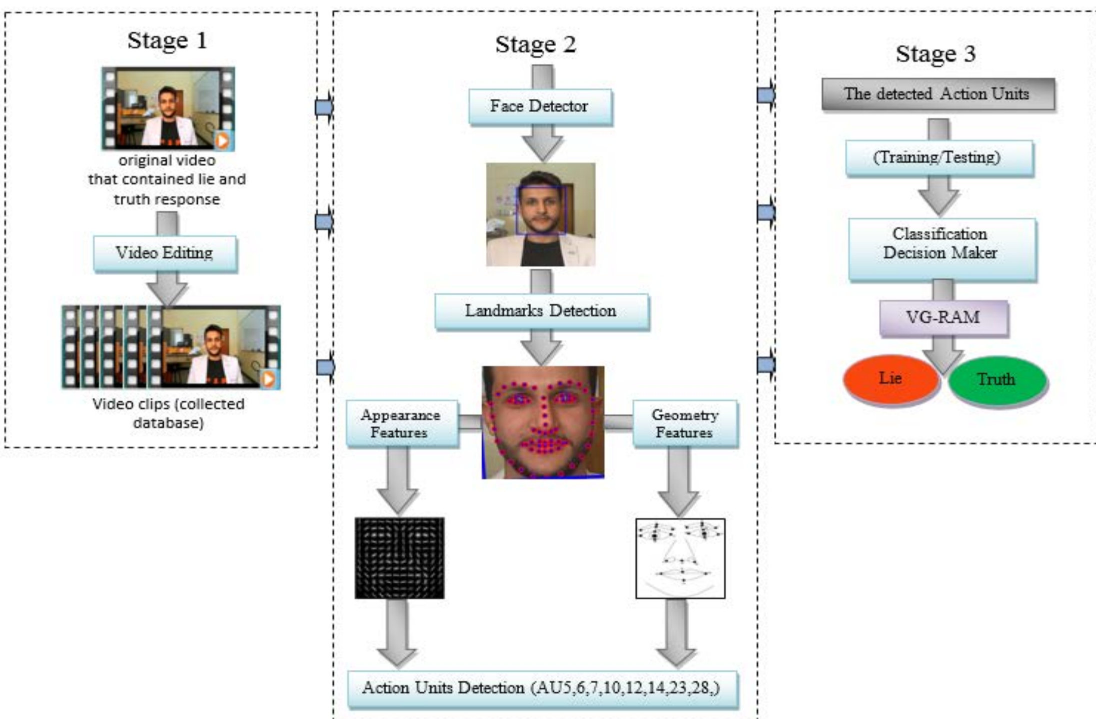

Fig. 3: Stages layout of proposed deceptive detection system

of the proposed system. Finally, VG-RAM classifier is used for decision maker to identify the subjects were lying or telling the truth this represent stage 3 of the proposed system.

Collected database: To date, deceptive detection research used a few datasets and none of them were publically available, so, to design a deception detection its required to collect database in order to measure the system performance.

The datasets were collected from 43 participants (20 males, 23 females) between the ages 18-25 during the interview each participant was asked a set of 27 equations (8 control questions and 19 relevant questions) according

Fig. 4: The interview session. The subject's facial expression recording while the examiner is asking the questions

to Anonymous (2007). All questions are asked and repeated for truth and lie reactions while the camera Sony Cyber-shot was recording the facial behavioral during all session as shown in Fig. 4. The questions are:

Control question:

- Is your name Ahmed/Sara?
- Are you 40 years old?
- Do you have Iphone mobile?
- Do you live in Karada?
- Is today (day of week)?
- Are you born in 1976?
- Do you have a breakfast today?
- Did you take a shower yesterday?

Relevant question:

- Did you fall in an exam and did not tell your parents?
- Has anyone cheated you before?
- Sony Cyber-shot one day did anyone bead you in a public place?
- Has anyone harassed you in a public place?
- Do you feel stupid sometimes?
- Have you stolen more than 25 thous. Iraqi dinars?
- Who is the friend that spoke about him in his absence?
- Have you ever committed a negative act against anyone?

  Did you ever put false information on an official document?
- Do you revealed the secret of someone who trusted you?
- Did you ever take credit for something you didn't do it?
- Did you ever deceive a family member?
- Did you cheat on the exam?
- Who is the teacher in your opinion hated?
- Who is the teacher in your opinion beloved?
- Who is the teacher in your opinion needs to hit hard?
- Who is the teacher in your opinion can not deliver the information to his students correctly?
- Who is the teacher in your opinion is trivial?
- Who is the teacher in your opinion arrogant?

The video of each subject was cutting into a set of video clips with average length 1 sec using Windows Movie Maker program. Each video clip content the duration when the subjects thinking before answer the questions. These video clips included some parts of original videos that content the effective and subtle muscles movements of the original video for certain expression. In total, the number of clips that obtained from all original videos are 400 video clips: 200 for lie response and 200 for truth response where 200 video clips belong to male participants (100 for lie response and 100 for truth response) and 200 video clips belong to female participants (100 for lie response and 100 for truth response).

The datasets are collected in normal lighting condition, backgrounds are highly variable and there are no restrictions on the head movement of the participants, the participants move their heads freely without restrictions during the all interview, the collected datasets are content natural facial expression during lie and true responses instead of being acted or contrived.

Feature extraction and action units detection: The proposed DDS is extract features based on detecting some facial AUs which represent different muscles movements of the face. Table 1 summarizes eight AUs that used in this research as potential indicators to discriminate liars from truth-tellers. These AUs are chosen because it is most affective facial AUs during lie and true responses based on collected database, after detecting AUs of all collected database discern that these chosen AUs are very clearly affected during both responses and other facial AUs did not have a clear impact on the recognition rate based on collected database. The overview of AUs detection method is illustrated in Fig. 5.

Input video clip captured by camera (25 FPS) is broken to a set of frames. Next step is face detection to detect the face of a subject by using Viola-Jones detector. The facial landmark was detected using CLNF approach that given the location of 68 landmarks which is represent the important facial features for emotion recognition.

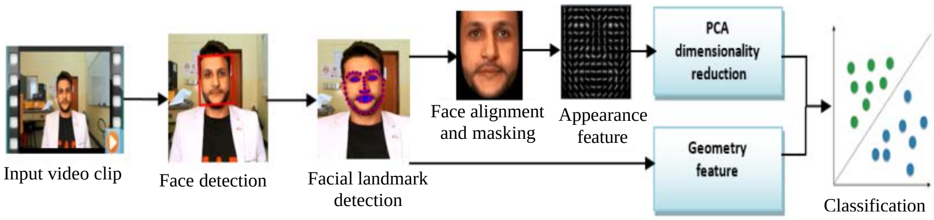

Fig. 5: Overview of AUs detection method that used for features extraction of the proposed DDS

Table 1: Effective AUs with its name and region based on FACS

Action units	FACS name	Facial region
AU5	Upper lid raiser	
AU6	Cheek raiser	
AU7	Lid tightener	
AU10	Upper lid raiser	
AU12	Lip corner puller	
AU14	Dimpler	
AU23	Lip tightener	
AU28	Lip suck	

Table 2: The datasets division that used in each experiment

Gender/Experiment	Number of participants	Number of video clips	Number of video clips for lie response	Number of video clips for truth response	Number of training sets video clips that chose randomly	Number of testing sets video clips
Male and female (1)	43	400	200	200	200(100 lie/100 truth)	200(100lie/100truth)
Male only (2)	20	200	100	100	100(50 lie/50 truth)	100(50 lie/50 truth)
Female only (3)	23	200	100	100	100(50 lie/50 truth)	100(50 lie/50 truth)

Face alignment and masking is necessary to map the face to a common reference frame and to eliminate the non-facial information from the image. HOGs used to code the face image to extract the appearance features from it. The Principal Component Analysis (PCA) is used to reduce dimensionality of HOG feature vector, the purpose of this reduction is to obtain more generic training model. The geometry based features represent the non-rigid shape parameters and the landmarks positions. Finally, SVM classifier is used for AUs detection that used linear kernels function where various datasets used to train it.

Classification: After detecting AUs for each input video clip, the classification is employ to categorize AUs into two classes (lie and true classes) based on extracted facial features during lie response and true response. Among several classifiers, VG-RAM WNN classifier is chosen.

Corresponding to AUs of 400 video clips (200 video clips for lie response and 200 video clips for truth response) the dataset was divide into two groups, first group (100 video clips for lie response and 100 video clips for truth response) for training the classifier and the second group (100 video clips for lie response and 100 video clips for truth response) for testing the proposed system. The training sets are chosen of randomly for lie and true response. Others two test of proposed system when separate male subjects and female subjects using collected datasets, first time used only male datasets 20 participants that consist of 200 video clips (100 belong to lie response and 100 belong to true response) where half of this datasets used for training. The second test used only female datasets 23 participants that consist of 200 video clips (100 belong to lie response and 100 belong to true response) where half of this datasets used for training. Table 2 shows the datasets division that used for testing the proposed DDS.

RESULTS AND DISCUSSION

The performance result of proposed DDS is shown in Table 3. The datasets were divided as mentioned in the previous study. The result show that system classify 90 samples out of 100 samples correctly regarding to lie response and the rest 10 samples were classifying wrong as truth class. Moreover, 78 samples out of 100 samples are correctly classify regarding to truth response and the remain 22 samples were classifying wrong as lie class. The overall accuracy was 84% of detecting liars for both genders.

Table 4 shows the result of proposed system based on only males gender datasets, system classify 44 samples out of 50 samples correctly regarding to lie response and the rest 6 samples were classifying wrong as truth class. Moreover, 46 samples out of 50 samples are correctly classify regarding to truth response while only 4 samples were classifying wrong as lie class. The accuracy was 90% of detecting liars for male participants.

Table 5 shows the result of proposed system based on only females gender datasets, system classify 42 samples out of 50 samples correctly regarding to lie response and the rest 8 samples were classifying wrong as truth class. Moreover, 43 samples out of 50 samples are correctly classify regarding to truth response and the remain 7 samples were classifying wrong as lie class. The accuracy was 85% of detecting liars for female participants.

Table 3: Result of proposed system based on VG-RAM using male and female datasets 400 video clips (200 training/200 testing)

	The output class of the classifier	
The actual class	Lie	Truth
Lie	90	10
Truth	22	78
System recognition	84%	

Table 4: Result of proposed system based on VG-RAM using only male datasets 200 video clips (100 training/100 testing)

	The output class of the classifier	
The actual class	Lie	Truth
Lie	44	6
Truth	4	46
System recognition	90%	

Table 5: Result of proposed system based on VG-RAM using only female datasets 200 video clips (100 training/100 testing)

	The output class of the classifier	
The actual class	Lie	Truth
Lie	42	8
Truth	7	43
System recognition	85%	

The results are comparing with previous researches as show in Table 6. From this table the high accuracy was achieve is 90% in the 20 subjects of the proposed system comparing to the high accuracy of previous research 85% in the 4 subjects (Owayjan *et al*., 2012), same accuracy 85% was achieve by proposed system in the 23 subjects. The accuracy of proposed system was 84% in the 43 subjects (400 video clips) comparing to the 70% in the 50 subjects (Singh *et al*., 2015) and 76.92% in the 324 video clips (Su and Levine, 2014). As a final result, the proposed system is superior to all previous researches, although, the dataset used is larger compared with previously datasets.

Hardware implementation: To build the overall proposed deceptive detection system required many hardware functionally, large memory and may require many hardware circuit this, so, difficult to implement in the available laboratories and devices. The suggestion to solve this difficulty is to implement only the VG-RAM classifier, it is a neural network classifier required only memory to store the training sets and simple arithmetic operation used to calculate the minimum hamming distances, it can implement as FPGA model due to its simplicity. When implement this classifier on FPGA kit it is necessary taking into account the size of RAM, this is considering as one of the hardware problems be face with FPGA implementation for such classifier. In this research, the training sets used to learn the VG-RAM are consisting of 200 visual feature vectors that can be treated by the FPGA platform used in this research, so, the size of memory was within the limitation of requirement.

The proposed deception detection classifier VG-RAM is built as FPGA model using Simulink Xilinx library in MATLAB-2012a based on system generator block. Figure 6 shows the block diagram of the proposed VG-RAM classifier that train and test based on all collected datasets (male and female participants). The constant block F is source block parameters that represent the input feature vector which want to classify belong to lie class or truth class based on training datasets that store in the ROM Xilinx block. The number of training

Table 6: Results comparison based on number of participants and the accuracy

Ref. No.	Types of features	No. of participants	Accuracy (%)
Jain *et al*. (2012)	Thermal imaging	16	83.5
Azar and Campisi (2014)	Temperature change	11	84
Singh *et al*. (2015)	Eye blinkcount (AU45)	5	---
George *et al*. (2017)	Eye blink count and duration (AU45)	50	70
Owayjan *et al*. (2012)	Facial micro-expressions	4	85
Su and Levine (2014)	Facial expressions based on six AUs	Database collect from YouTube 324 video	76.92
Proposed system	Facial expressions based on eight AUs	43(400 video clips)	84
		23(200 video clips)	85
		20(200 video clips)	90

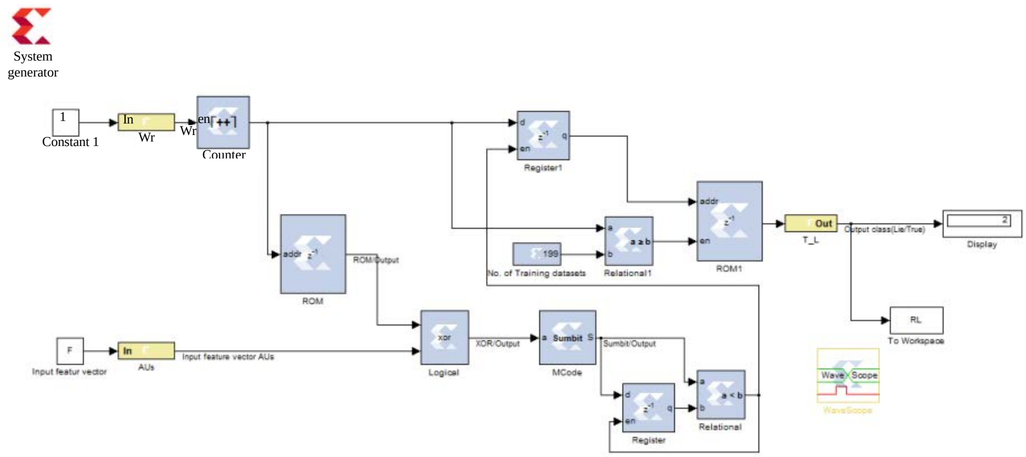

Fig. 6: FPGA Model of the proposed VG-RAM classifier

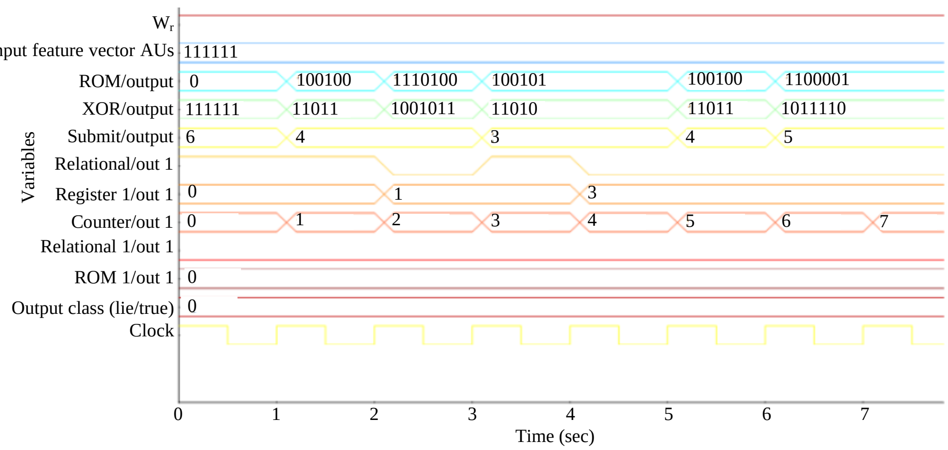

Fig. 7: The simulation behavioral of the VG-RAM classifier

datasets was 200 feature vectors that store in the first 200 bytes of the ROM. The XOR Xilinx logical block and Sumbit Mcode block are used to calculate the hamming distance between the input feature vector and all feature vectors stored in the ROM where the minimum hamming distance is chosen based on Xilinx register and relational blocks. ROM1 store (2×200 bits) the classes of each feature vector in the training datasets. Xilinx counter block is used to provide the address of ROM when system calculates the hamming distances. Xilinx rigister 1 block used to hold the address of feature vector that has minimum hamming distance with the input tested feature vector. The Xilinx constant 2 and relational 1 used to inform the system that all hamming distances are calculated and chosen the minimum one to give the output class of the input tested feature vector. Table 7 shows the output signals that given by classifier.

The simulation behavior of proposed VG-RAM FPGA model is shown on Fig. 7 where the wr signal indicate the input feature vector that wanted to be classify is available, this wr signal enable the counter to beginning provides the address of the training datasets that store in the ROM, the purpose from this counter is producing the address of all features sequential to calculate the hamming distance between the input feature vector and all feature vectors stored in ROM. According to simulation behavioral results for each high rise clock the counter is increase by one count to given the address of next feature vector stored in ROM.

Table 7: The output signals of the deception detection system

T-L output	Deception detection system
00	Wait for visual feature vector
01	True
10	Lie
11	Wait for visual feature vector

The output of ROM is given the feature vector corresponding to input address. The XOR and sumbit Xilinx blocks calculate the hamming distance between the input feature vector and the feature vector given by ROM at certain clock. For each given hamming distance the output of Sumbit Xilinx block compare with the hamming

Table 8: Device utilization summary of the VG-RAM classifier

Device utilization summary

Logic utilization	Used	Available	Utilization (%)	Note(s)
Number of slice flip flops	20	11.776	1	
Number of 4 input LUTs	45	11.776	1	
Number of occupied slices	28	5.888	1	
Number of slices containing only related logic	28	28	100	
Number of slices containing unrelated logic	0	28	0	
Total number of 4 input LUTs	52	11.776	1	
Number used as logic	45			
Number used as a route-thru	7			
Number of bonded IOBs	12	372	3	
Number of BUFGMUXs	1	24	4	
Number of RAMB16BWEs	2	20	10	
Average fanout of non-clock nets	2.96			

distance stored in Register Xilinx block that represent minimum hamming distance of the previous feature vectors stored in ROM. This comparison is done using relational Xilinx block, the output of the relational Xilinx block goes high when the current hamming distance is less than hamming distance stored in register Xilinx block as shown in Fig. 7, this lead to enable the register Xilinx block to store current hamming distance (minimum) instead of pervious hamming distance and enable the register 1 Xilinx block to store the address of the feature vector (the address of ROM) that given this minimum hamming distance.

After calculate all hamming distance and chose the minimum one the system stores the address of feature vector that given this minimum hamming distance in register 1 Xilinx block and produce the output class of the input feature vector that want to be classify. The classifier will complete the classification of certain unknown pattern after 200 clocks. The hardware results are confirmed the simulation results shown in Table 3-5. The design summary of the implemented VG-RAM classifier, the proposed classifier takes only 20 from available occupied slice flip flops which is <1% of Spartan-3A 700A, also, takes only 12 of the bounded input/output that represent only 3% of the 372 pins while the total number of 4 input Lock-Up-Tables is 52 which is <1% of the hardware platform which is summarized in Table 8. According to timing summary, the maximum frequency allowed for VG-RAM classifier is 96.08 MHz. Therefore, this system needs approximately 2.0816 μsec to finish classification of one input feature vector.

CONCLUSION

The experiment results prove the theory of the facial expressions can be used for spotting liars. The main purpose of the proposed system is to detect real facial muscle movement and adopt it as reliable indicators to separate lairs from truth-teller in unconstrained environments using eight AUs (5, 6, 7, 10, 12, 14, 23 and 28) which are the most effective facial AUs on detecting liars based on collected database. The database that used in this experiment was rather challenging. It is possible to obtain better result if the datasets are collect in real-world situations (actual police interrogation scenario) this will give a more reliable and more natural facial clues for deception detection.

The results are very promising. The correct classification accuracy using 1 sec video sequences was 84% in the 43 subjects. The accuracy has increase a bit when the proposed system tested using database of female subjects which consist of 23 participants, the accuracy was 85%. The best accuracy was achieved when test the proposed system using database of male subjects which consist of 20 participants, the accuracy was 90%. The results of hardware systems confirmed the simulation results with high speed of training and testing. The time that is taken for testing the hardware system in unknown sample was 2.0816 μsec.

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