3D FACE RECOGNITION RELATED WITH FACIAL EXPRESSIONS BASED ON MB-LBP METHOD

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ABSTRACT

3D Face Recognition is a promising alternative to solving problems of 2D recognition. Our proposed approach allows, increasing the performance of facial biometrics by offering a system of recognition of facial expressions with 3D image. This system uses a flow composed simultaneously of a color image (2D) and a depth image (3D) captured by the Microsoft Kinect sensor. Our system detects, and identifies the expression of the captured face; then recognize the seven expressions developed by Paul Ekman using the MB-LBP method. We have introduced a new dataset corresponding to 10 human subjects [23, 27] for learning step with a classification using SVM method. The implementation of our solution produces in C^{++} using the OpenCV library.

KEYWORDS: Face recognition, facial expressions, Kinect, MB-LBP, SVM.

1 INTRODUCTION

To improve the dialogue between man-machine, several researchers have concentrated on the analysis of the human face and several works specialized in the study of facial expressions. Many extensions have been made in 2D and video image acquisition systems and techniques to improve face analysis approaches such as detection, tracking, recognition and synthesis. These developments typically improve the identification of facial expression. However, the success of treatment of facial expressions has certain problems such as variations in lighting conditions, changes in head pose and partial occlusions [3].

In the future the 3D cameras, a new facial modality will arise in the field of computer vision. This is the 3D geometry of the face. The acquisition of data is more complete so the face analysis was able to cope with the modifications of pose and illumination. Nevertheless, the price of these scanners is very expensive and their configuration is delicate [3].

The famous technique of face detection in the last decade is that proposed by Paul viola and Michael Jones (Viola & Jones) in 2001 [1, 2]. This method combines four key principles that are the simple rectangular features called pseudo-haar features because of their similarity to Haar wavelets, Several researchers have drawn inspiration from the "Viola & Jones" approach, while proposing changes in the pseudo-haar extraction characteristics and / or in the use of the doping algorithm in order to improve the facial detection Lienhart and Maydt propose a first improvement [4] of this technique in 2002. In 2003, Viola and Jones improved their initial method to deal with the problem of multiple face detection at the same time.

The next phase is the recognition of the facial expressions which is also the subject of several works in the field of vision by computer [5]. Automatic recognition of facial expressions consists of two steps which are characterization and comparison or classification techniques are used to make either a measure of similarity (resemblance) or a distance measure (divergence) such as Euclidean distances , Mahalanobis,…[3].

Like an automatic biometric system, an automatic facial expression recognition system operates in two modes [7]: verification mode from 1 to 1 and identification from 1 to N. The result of this system is the identification of the expression or a message indicating the recognition failure.

According to Albert Mehrabian [18], the facial expression of an interlocutor accounts for 55% of the effect of an oral message and the intonation of the voice contributes to 38% while the verbal part has only 7% effect. From this are inspired several works which are oriented towards the study of the facial expressions in particular the recognition and the reconstruction.

The facial expression is a testimony of what happens inside a person in relation to the textual content as evidenced by the research work of Mehrabian [18]. As approaches based on 2D facial models suffer substantial limitations to the variation of pose and illumination, we will take advantage of the technological advances of 3D scanners and the possible combinations between the 2D and 3D facial modalities to implement our approach [3]. To do so, we will use the Microsoft Kinect sensor, which is a natural interaction device allowing the simultaneous capture of a RGB (2D) and depth (3D) flows, and we propose to use the MB-LBP (Multi-block Local Binary Pattern) in the phase of recognition of the facial expressions; which has the property to capture micro and macro structure information [22].

The literature presents an important number of techniques that deal with the recognition of facial expressions; however we are only interested in those that are always present in the related works. Before going any further it is essential to note that several techniques deal with both face detection and its components and recognition of face and facial expressions [3].

In the second section we detail according to these techniques those the most important in our research.

2 RELATED WORKS

In the following we will present the related works with the facial detection and 3D reconstruction that we have based on;

2.1 Description of Facial Detection

In 1991, Turk and Pentland [6] the PCA makes it possible to identify the congruent characteristics that identify a multidimensional data set while reducing the size of the data. In 1997, Belhumeur et al. [8] propose an alternative to the "eigenfaces" approach under the name "Fiserfaces", The support vector machine technique known as SVM (Support Vector Machine) is proposed by Vladimir Vapnik in 1995. Zhang et al. [10] Use neural networks for the recognition problem of facial expressions, Cohen et al. [11] Present a multi-level HMMS method for the segmentation and recognition of facial expressions from a video sequence their approach reaches a recognition rate of about 82.46% for a familiar person and a rate of about 58.63% for an unfamiliar person.

The Active Model Appearance Recognition (MAA), technique was proposed in 2001 by Cootes et al. [9]. Among the works that study the recognition of expressions by active models of appearances, gives an overall recognition rate not very different: 84,34% for the basic model and 83,73% for the hierarchical MAA [12].

2.2 Description of the 3D reconstruction

3D reconstruction consists in recovering the geometry of the scene observed by the vision system in its real dimensions. This reconstruction consists of three sub-steps: calculation of the point cloud to 3D, interpolation of these points by an algorithm of meshes among those available to recover a shape having continuity and the last sub-step is the texturing of the obtained form. [3]

The reconstruction of facial expressions is studied in the 2D domain by Abboud et al. [13]. The reconstruction of a 3D face model is examined by Kemelmacher-Shlizerman et al [16]. These authors proposed a method capable of recovering the 3D shape of a face from a single image.

Zollhöfer et al. [14] propose a fully automatic method to build a custom avatar (3D face model with texture) with high quality from the simultaneous capture of a single colored image and the corresponding depth image by making use of the Kinect sensor of Microsoft and a 3D model morphable.

Weise et al. [15] propose a system that captures and tracks the dynamics of facial expressions of users in real time and draws them to a virtual model the Kinect sensor as well. The proposed system integrates the path and the animation in a single optimization and shows that the 3D reconstruction of the face and the animation of the face can be realized in real time without using the markers on the face of the user [3].

B.Seddik and H. Maâmatou [29] propose in 2013 a solution capable of recognizing the facial expressions performed by a person's face and mapping them to a 3D face virtual model with the depth and RGB data captured from Microsoft's Kinect sensor using their obtained dataset; Kinect Facial Expression (KiFaEx). The developed solution offers the advantage of unsupervised expression reconstruction from the sensor and shows near to the state of the art performances [29].

In 2013, Y. Sun, X. Wang and X. Tang [30] propose a hybrid convolutional network (ConvNet)-Restricted Boltzmann Machine (RBM) model for face verification in wild conditions. This work directly learns relational visual features, which indicate identity similarities, from raw pixels of face pairs with a hybrid deep network. The hybrid deep network is jointly fine-tuned to optimize for the task of face verification. This model achieves competitive face verification performance on the LFW dataset [30].

In 2014, Y.Sun, X.Wang and X. Tang [31], propose to learn a set of high-level feature representations through deep learning, referred to as Deep hidden IDentity features (DeepID), for face verification. DeepID features when learned as classifiers to recognize about 10, 000 face identities in the training set. The proposed features are extracted from various face regions to form complementary and over-complete representations. Any state-of-the-art classifiers can be learned based on these high-level representations for face verification. 97.45% verification accuracy on LFW is achieved with only weakly aligned faces [31].

In 2016, D.Aneja and A.Colburn [32] propose DeepExpr, a novel expression transfer approach from humans to multiple stylized 3D characters. They first train two Neural Networks to recognize the expression of humans and stylized characters independently. Then, they utilized deep learning techniques as a tool to extract useful features from raw data for both human faces and stylized characters. In the last step of classification, the algorithm attempts to classify the given face image into seven different classes of basic emotions using machine learning techniques. SVMs are most commonly used for Face Expression Recognition tasks [32].

3 VIOLA ET JONES AND MB-LBP: METHODS USED FOR DETECTION AND RECOGNITION

In the following we will present the detection method of Viola & Jones and the Recognition by the MB_LBP method;

3.1 Detection Method Viola and Jones

The "Viola & Jones" method was originally proposed for the detection of faces in a digital image or video sequence and then used to detect other objects such as cars ... The OpenCV library presents an implementation of this method under the name "Detector in cascades de haar" [3].

This method combines four key contributions which are the pseudo-haar characteristics [17], the integral image [1, 2] approach, the adaptive learning method AdaBoost [26] and the cascading classifier algorithm [1, 2]. In the following, we will detail these key steps while specifying the contribution of each of them to the performance and effectiveness of the method [3]:

- The pseudo-haar characteristics allow the detection of objects in several scales (multi-scale detection).
- The integral image allows the calculation of the characteristics in real time.
- The AdaBoost algorithm selects the most discriminating characteristics for classification and forms a good performance classifier.
- The cascade minimizes computation time and refines classification boundaries.

3.2 Recognition by the MB_LBP method

MB-LBP (for Multi-block Local Binary Pattern) Li et al [19] proposed the Multi-Block LBP (MB-LBP) for face detection and recognition [20]. In MB-LBP, the comparison between the individual pixels in the LBP origin is replaced by those between the mean intensities of the sub regions.

More precisely, the MB-LBP operator compares the average intensity of the central sub region with the neighboring sub regions, the initial LBP can be considered as a particular example of MB-LBP. Fig.1 shows an example of MB-LBP, where each sub region is composed of six pixels. The sub region may be a rectangle or a square. The average intensities of more blocks possible be calculated very efficiently using the integral image. The effectiveness of MB-LBP has been guaranteed for both face detection and recognition tasks [21, 22].

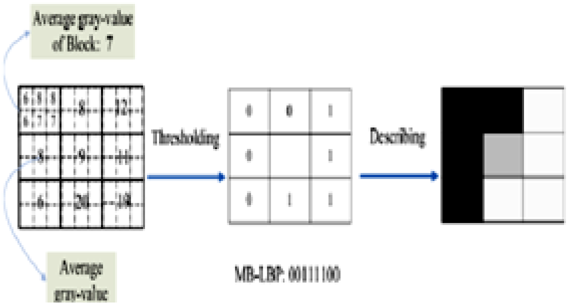

Figure 01: An example of the MB-LBP operator [21, 22].

Figure 02: Features MB-LBP for a face [24].

4 THE PROPOSED SYSTEM

Researchers seek to improve the reliability of authentication systems based on the fingerprint of the face. These include acceptance of the technology by the public, lack of direct contact, and low implementation costs. Unfortunately, the presence of facial expression complicates the task and disturbs the industrial adoption of this approach.

Our proposed approach allows, among other things, to increase the performance of facial biometrics by offering a system of recognition of facial expressions.

We will begin by giving the descriptive diagram of our proposed solution. Our results and experiments will be provided we will present the characteristics and the mode of operation of the Kinect then we present the details relating to the facial detection using the OpenCV library. Then we will go on to explain the principle of the Viola & Jones method and we will detail the approach of spatial segmentation of face adequate to the extraction of facial features by Eigen face. We will then show the recognition of the facial expressions by MB-LBP.

The purpose of comparing methods on a set of data is to test their ability to bypass the problems that the system may encounter in the real world 'good performance on these bases can be translated into good performance in real situations'. Several databases have been developed to meet the specific needs of the facial recognition problem. We based on main databases that have chosen about 10 persons in their dataset created for the problem of facial recognition, as example; the Facial Expression Research Group-Database (the FERG-DB) database is composed of 6 persons for 3D Facial Expression Recognition [23], Yale. B database is composed of 10 persons for 2D Face Recognition [28], the Japanese Female Facial Expression

(JAFFE) database is composed of 10 persons for 2D Face Recognition [27], Weinstein algorithm composed of 10 persons for 2D + 3D Face Recognition [22].

To achieve our goal, it is essential to have a database of all the expressions recognized by the system and a generic model that can present all these expressions. We have introduced a new dataset corresponding to 10 human subjects, each human subject have 10 images it includes images and point clouds to the various facial expressions performed for learning step.

4.1 Outline of the proposed system AREFK:

Our automatic expressions face recognition system with Kinect (AREFK) including seven steps: the acquisition of data followed by a pretreatment and the detection of the face. Then we have step of characterization followed by step five and six.

Step five serves to learn the characteristics of the expressions; step six allows the recognition of a test expression. Finally we have the Face and the expression identified.

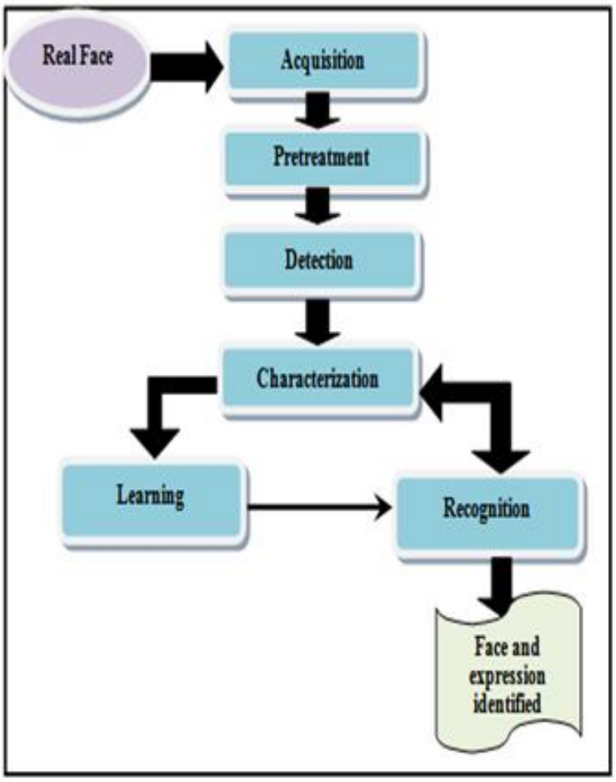

Figure 03: Outline of our proposed approach

In the following, we will detail each of these steps.

4.2 Overall description of the proposed system

The problem to solve with our approach is the developing of a system capable of detecting the face of a person with a frontal view and then recognizing its facial expression. To achieve our goal, it is essential to have a database of all the expressions recognized by the system and a generic model that can present all these expressions.

4.2.1 Data Acquisition

Data acquisition is the first step in our system of acquiring data from the real world. In our case, all input data is acquired via the Kinect systems. The latter tolerates simultaneous captures of a 2D color image and a 3D depth image.

4.2.2 Pretreatment and Face Detection

Step is necessary to improve the quality of the data acquired. It is decomposed in our system into two tasks: the calibration of the two cameras of the Kinect and the filtering of depth flux to represent only the useful information that is to keep only the data representing the face.

To calibrate the cameras of our Kinect, we have prepared a code allowing to alternate between these two modes to collect the images of the calibration pattern. Constraints were set by the following source code used: [3]

```
Fixed positioning of Kinect
  For i = 1 to 10
     Fixing i of the test calibration
     Enter to start the iteration
     Activate the mode RGB
     Capture and save 10 RGB images.
     Activate the mode IR
     Capture and save 10 IR images.
     Applying the filter to IR images.
     Write "fix your ecchi again.
   End For
```

In order to determine the parameters of the cameras (RGB and IR) of our acquisition device, we use a source code developed by Nicolas Burrus which uses certain functions of the OpenCV library implements the "Viola & Jones" face detection method and results six ".XML" files representing the Matrix K called haar cascade files, the disparity matrices of the Kinect cameras, the rotation matrix and the position vector of the Kinect.

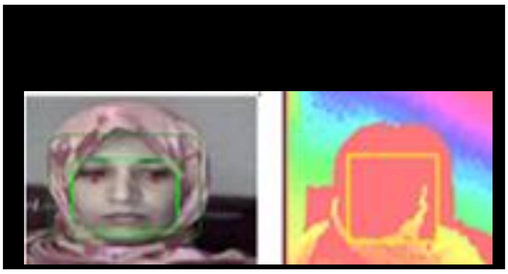

Figure 04: Shows the importance of calibrating the cameras before any data retrieval from depth flows

In this framework, we have devoted a first sub-step to the detection of the face in order to differentiate its presence / absence, to continue its localization by an encompassing rectangle and to recognize the different features of facial expressions by rectangles

After detecting the face, we used the geometric approach to locate the regions containing the significant elements of the face such as the mouth, the eyes, and the nose by a "geometric approach".

In the second, we limit ourselves to the depth flux on which we perform a thresholding to remove the additional information inside the drawn rectangle, we use the (cvThreshold) function offered by OpenCV.

Based on this distribution, we proposed a spatial segmentation of the face, the result of which is given in Fig.6.

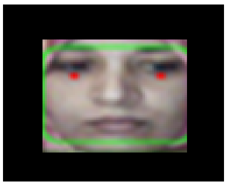

Figure 05: Face parts detection and extraction

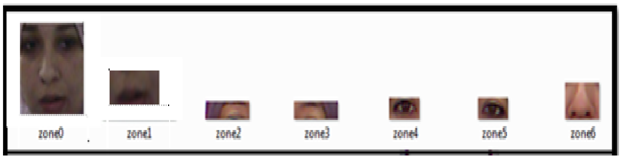

Figure 06: A spatial segmentation of the face

4.3 Characterization

The characterization step creates a list of images called "Eigen Faces" whose number equals the number of images of the base. In our case, we call an output image of this step an "Eigen Expression" view that presents the relevant elements that distinguish between the different expressions of our database. Once the Eigen Expressions are constructed, we will determine the series of weights of each image of our base. In other words, we compute the coordinates of each expression in the space generated by the Eigen Expressions elaborated.

4.4 Recognition

The recognition process is based on two previous phases of characterization and learning. It involves multiple images of faces with associated expression classes.

To identify the expression of the person present in front of Kinect, we first tested the image database. Then we chose to create our own base of expressions in order to escape the limit classification during an interclass variability associated with a wide variability of light within the same class. The recognition of the face expressions will by using MB-LBP method.

Figure 07: Shows examples of the facial expressions of our database

This phase of the "MB-LBP" method, saves only the average intensity of the central sub region with the neighboring sub regions which are the first X intensity vectors in the form of a so-called "intensity matrix". In this step, we extract the face of the user, then we calculate the intensity vector of the expression presented by the captured face and finally we compare the result vector with each column of the intensity matrix. We determine the class of the test expression based on the minimum Euclidean distance as a comparator between the query vector and the reference. Having a minimum distance between the test vector and one of the columns of the intensity matrix indicates that the image corresponding to the latter vector is closest to the test image and its identity is that of the test expression.

4.5 Learning

Our system requires a learning phase; we used the learning by exploiting the profile and frontal face classifiers offered by the OpenCV library. During the latter, there will be a collection of information on expressions to be identified and their saving in the form of easy-to-use descriptors.

In our case, a descriptor is a weight vector that describes the weights of each image in the space of proper faces. We have retained only X proper faces among those generated so we will have X vectors of weights which will be saved in the form of a matrix called weight matrix using classifier evaluated in a file with the SVM (Support Victor Machine) method by exploiting the classifier intended to detect a particular face when it is present in frontal view.

SVM Technical supervised classification derived according the theory of statistical learning. The essential idea is to project data belonging to different classes not linearly separable, with the input space, in a larger space called feature space, so that the data becomes linearly separable [25].

In this space, the optimal hyper plane built in technique is used to compute the ranking function separating the classes.

Case of two classes:

$\{(x_1, y_1), \ldots. (x_n, y_n)\}$ Where $y_i \in \{-1, +1\}$ and x_i input (1)

Then, this classifier is a hyper-plane maximizes the margin of error, which is the sum of the distances between the hyper-plane and (positive, negative) examples of the closest hyper-plane [25]; requires classification of these two classes applied the SVM method that was presented previously.

In the case where the data cannot be separated with a linear function, a non-linearity can be introduced by using a no-linear function.

5 EXPERIMENTAL RESULTS

In this section we present two different interfaces of our system, the first visualize the flow captured and the next shows the recognition of the expression related with the face.

5.1 Presentation of the interfaces of our System

The first interface displayed our system shown in Fig.8 which serves to visualize the flow captured by the Kinect. Once the "Charging Faces" button is pressed, this last action also launches face detection in the displayed image, eliminating unnecessary information in both images, drawing the rectangles encompassing the face in the corresponding color image and depth image and tracking the movement of that face in the scene.

Figure 08: Flow visualization interface captured by the Kinect

The button "Learning" allows the construction of a learning image takes place. The result of this last act is the creation of two files simultaneously: a file ".bmp" presenting only the detected face, this file is saved in a directory created in advance and shown in Fig.7. In addition, a file ".dll" using functions of the OpenCV library, presenting the cloud of points corresponding to the associated depth image.

Now to the button "Charging model 3D", this button is used to create the list of Eigen Expressions relating to the images of our database, to calculate the weights of each image of our database and finally to save the result matrix in a file which will be used in the recognition process. The same button also serves to update the weight matrix and the Eigen Expressions list once created and charge the 3D model expression associated to the face detected.

Once we have a file showing the weight vectors of each image of the learning set we can test our system via the interface shown in Fig.9

The Fig.9 showed our interface which serves to visualize the recognition of a face then the expression related with it after clicking on the "Recognition" button. During the execution scenario, this interface, displays the captured color and depth image. In addition to displaying the interface, this button is used to detect the face present in the scene, resize the image to match fixed size for learning images, convert it to grayscale, and calculate corresponding intensity vector. It also uses a function that compares the calculated intensity vector with the matrix saved in the file using the Euclidean distance. This last function returns the name of the class whose associated column is closest to the test vector.

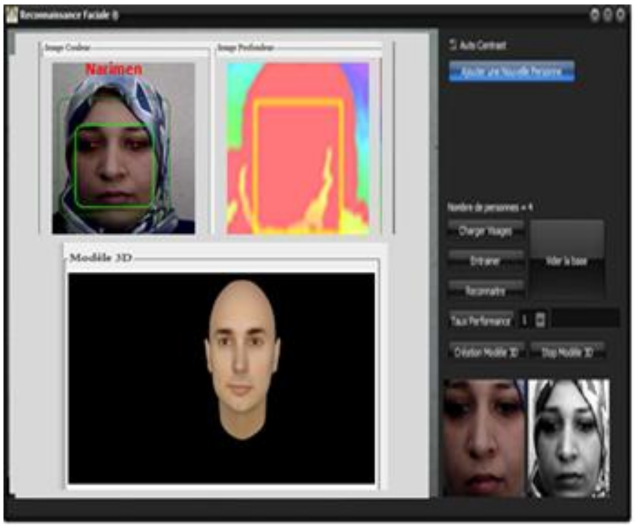

Figure 09: Interface showing the recognition expression of the face detected in the scene

5.2 AREFK dataset description

Our automatic expressions face recognition with Kinect (AREFK) dataset of images and point clouds contains information relative to 10several subjects with each one seven different expressions. (Fig.10 displays examples between them using with FERG database).

Several shots were gated approximately for every reaction, only some data was used for expression accuracy reasons. The selected faces were separated to 70 expressions used for the learning process and 42 other ones used for the test.

The data acquisition was collected in a fixed position below the same lighting conditions to get the best results rates of recognition.

Figure 10: Facial Expression Research Group Database (FERG-DB) [23].

Table I shows an example which is based on the evaluation of 10 persons and 10images/person with seven different expressions retained for the test stage. The best found average percentage is 97% corresponding to the 6th person.

Table 01: Table showing OUR DATASET Recognition

Persons	*Data set of AREFK system*						
	Neutral	**Fear**	**Disgust**	**Anger**	**Surprise**	**Joy**	**sad**
Person 1	3	9	-	8	3	2	11
%	89%						
Person 2	10	3	2	1	4	12	-
%	95%						
Person 3	-	2	7	1	-	8	1
%	93%						
Person 4	1	5	-	6	1	3	-
%	87%						
Person 5	-	-	1	6	9	1	9
%	82%						
Person 6	13	-	-	-	2	7	-
%	97%						
Person 7	2	-	3	5	1	-	4
%	82%						
Person 8	-	5	2	3	10	9	-
%	79%						

Person 9	2	1	-	3	6	-	7
%	85%						
Person 10	3	-	-	4	7	-	2
%	86%						

6 METHOD COMPARAISON

Our goal with human expression accuracy is to attain a good result on the expression recognition that is adjacent to the state-of-the-art results so as to extract pertinent features relative to a facial expression.

In reason to judge the effectiveness of our system, we compared AREFK to a human expert. We asked the expert and compare their answers with the results of our system AREFK according to human query image.

We observe that a lot of incorrect classifications are due to logical similarities in the expression formulation. On an average, neutral, joy and surprise had similar recognition performance. For instance, disgust is practically similar to sadness in many cases. AREFK showed great improvement in recognition of sadness and disgust.

Fear was confused with surprise and the neutral state due to the similarity on geometric landmarks of the face showing an open mouth and eyes dispositions and disgust was easily confused with anger. Sad and anger, the closed mouth was easily confused with neutral. AREFK is acceptable by the implementing user; it obtained more (79%) expression recognition accuracy as compared to a human expert (90%).

The Table 2 summarizes the average expression recognition accuracy for each expression across all expression using human expert and our system AREFK.

Table 02: Average expression recognition accuracy (%) for each expression across all expression using a human expert and AREFK

Expression	Human Expert	AREFK
Neutral	**90**	**89**
Fear	**94**	**63**
Disgust	**83**	**76**
Anger	**96**	**77**
Surprise	**80**	**84**
Joy	**99**	**94**
sad	**92**	**71**

The Table 3 summarizes the performance of our AREFK dataset, compared with the KiFaEx dataset [29] and the results obtained by combining KifaEx & JAFFE dataset [27], we note that our performance, yielding satisfactory results, average accuracy percentage is 79% compared with the two other datasets 64%, 81% respectively.

Table 03 shows the performance of OUR DATASET RECOGNITION and other published datasets.

Dataset	Average Accuracy Percentage (%)
1- KiFaEx Dataset	64
2-KifaEx & JAFFE Dataset	81
3- **AREFK Dataset "Our Dataset"**	**79**

7 CONCLUSION DISCUSSION AND FUTURE WORK

We have presented, throughout this paper, the details concerning our solution and its implementation. We are only interested in the type of view methods, we have used Microsoft Kinect sensor consisting of two video cameras and depth. Throughout this research, we organized our effort on three steps: First we were interested in the recognition of facial expressions using the "MB-LBP" method. In the second step, we used the weight matrix provided by the learning step to automatically determine the facial expression visualized by the user, in the last we have presented the different interfaces composing the application in C^{++} produces our research. Although the proposed solution could improve and facilitate research in the human-machine interaction domain because it is a fully automated approach to face extraction and its characteristics, recognition of expressions Facials some deepening are useful.

In our future works, we interest focused on the reconstruction of the 3D model of the face, and mapping/ morphing of the expression visualized to that identified. In other words, we will have a change of form of the model visualized towards the form of the model representing the identified expression. Then, we will focus to use the deep learning techniques to perform the useful extraction features from raw data for both human faces and their representing expression model.

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