Robust Facial Expression Recognition Using Evidential Hidden Markov Model

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Applied to medical videos sequences analysis

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ABSTRACT. A great challenge of practical significance in a recent research topic is to develop computer vision system which can automatically recognize a variety of facial expressions. Such an automated system enables to detect faces, analyzes and interprets facial expressions in a scene although the accomplishment of this task is rather strenuous. There are several related problems: detection of an image segment as a face, extraction of the facial expression information, classification of the expression (e.g., in emotion categories) and their recognition. In this paper, we proposed system that performs facial expression recognition using an Evidential Hidden Markov (Ev-HMM) model in order to manage efficiently the constraints related to facial expression recognition problem. An application of this method as part of improving the monitoring system in medical intensive care units is carried out through to analysis and interpretation of the patient face behavior. The experimental results are very exciting and have shown a promise of our automatic recognition system.

KEYWORDS: Face Detection, Facial Expression Information Extraction, Facial Expression Recognition, Hidden Markov Model, Transferable Belief Model Framework (TB¨M).

RÉSUMÉ. Un défi majeur et d'application importante sur un axe de recherche très actuel est le développement de système automatisé en vision par ordinateur de reconnaître une variété d'expressions faciales. Un tel système intelligent permet de détecter les visages, d'analyser et d'interpréter les expressions faciales dans une vidéo bien que la mise en œuvre d'un tel système est une tâche est plutôt ardue. Des aspects connexes à la réalisation de ce système que sont, la détection d'un segment d'image comme un visage, l'extraction de l'information de l'expression du visage, la classification de l'expression (par exemple, dans les catégories de l'émotion) et enfin la reconnaissance de cette dernière doivent être traités. Dans cet article, nous avons proposé un système de reconnaissance d'expressions faciales en utilisant un modèle de Markov caché évidentiel afin de gérer de façon efficiente les contraintes de reconnaissance d'expression faciale. Une application de cette méthode dans le cadre de l'amélioration du système de surveillance dans les unités de soins intensifs médicaux est effectuée par le biais d'une analyse et d'interprétation du comportement du visage du patient. Les résultats expérimentaux sont très intéressants et ont montré une promesse de notre système de reconnaissance automatique.

MOTS-CLÉS : Détection de face, Extraction d'information d'expression faciale, Reconnaissance d'expression faciale, Modèle de Croyance Transférable.

1. Introduction

Facial Expression Recognition (FER) in video scenes is an important topic in computer vision, impacting important applications in areas such as video conferencing, forensics, biomedical applications such as pre or post surgical path planning or clinical improvement prediction, machine vision [1]. The most expressive way humans display emotions is through facial expressions and this latter provides cues about facial behavior. The aim of facial expression recognition methods is to build a system for the classification of facial expressions from continuous video input automatically. Furthermore, development of an automated system that recognizes facial expression is rather a difficult task. There are three main related problems for facial recognition system: detection of an image segment as a face, extraction of the facial expression information, classification of the expression (e.g., in emotion categories) and facial expression recognition. In this paper, we propose a system that detects the face while analyzing and interpreting the behavior of the face of a human in a medical video. Indeed, this system contributed significantly to the recognition of interest's events (critical health) that can improve the quality of the patient monitoring system in ICU [3]. An original application is proposed in order to assess the impact of the proposed method for patient monitoring in medical ICUS in cardiology section. Three main contributions can be noted in this work:

i) the first deals with the efficiency of facial expression recognition system based on robust approach by using an evidential HMM. This extension of the HMM allows to take into account at the same time several constraints of the system like physiognomic variability of the human, environment situation-dependent, timing of facial expressions that is a critical factor in the interpretation of expressions. The power of the proposed model lies in the ability and the potential of what the reasoning framework as transferable belief model. ii) The second contribution is related to the combination of facial expression information that uses the maximum intensity of the mouth on the one hand and on the other the maximum intensity of the eyes. iii) Finally, the field of applications is the originality of this work. For this, analysis and understanding of the scene in a video was not done in medical environment. In addition to this, a scenario such as *"fields the pain"* and *"anxious"* in a patient had never been studied.

The paper is organized as follows. In the first section, we describe our proposed method for facial expressions recognition in images sequences. To this end, we present at first, the face detection technique in image and then we explain how the facial expressions features are extracted. Finally, the last part of this section is to expose our robust and flexible algorithm for facial expressions recognition. Thus, after a briefly overview on Transferable Belief Model (TBM) framework [12], the main steps of evidential hidden Markov model for facial expressions recognition are presented. Section 3 is devoted for applying our approach to recognize facial expressions in medical video. The performance analysis of our method is done by comparing some experimental results with a baseline algorithm applied to various databases in section 4.

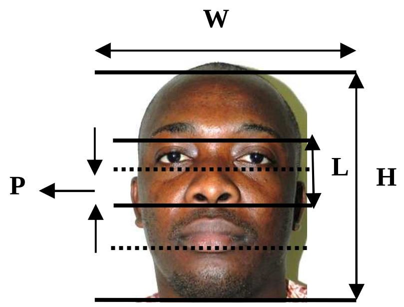
2. Proposed Method for facial expression recognition

Detailed review of existing methods on facial expression is seen in [6, 10]. A thorough study of the state of the art of existing methods on facial expression is proposed by Maja Pantic in IEEE transactions on pattern analysis and machine intelligence [panticPAMI00], and is also seen in [10]. Since the mid-1970s, many methods have been proposed for facial expression analysis and their recognition from either static facial images or image sequences. Among these, we have the approaches based on active contours, robust appearance filter, probabilistic tracking, adaptive active appearance model and active appearance model [1]. The aim of this section is to explore the issues in design and implementation of a system that could perform automated facial expression analysis. In general, three main steps can be distinguished for solving this problem. First step, before the analysis of facial expression, the face must be detected in a scene. The next step is to devise mechanisms for extracting the facial expression information from the observed facial image or image sequence. The final step is to define some sets of categories, which will be used for facial expression classification and/or facial expression interpretation, and to devise the mechanism of categorization. To this end, most facial expression recognition systems focus on only six basic expressions (i.e., joy, surprise, anger, sadness, fear, and disgust) proposed in the work of Darwin at the beginning [11] and more recently Ekman [11]. In everyday life, however, these six basic expressions occur relatively infrequently, and emotion or intent is more often communicated by subtle changes in one or two discrete features, such as tightening of the lips which may communicate anger. Facial expression recognition or human emotion analysis remains a very daunting task.

2.1. Face Regions Detection

In response to real-time system development and the homogenous processing system for facial expression recognition, we used Hidden Markov Model (HMM) to detect face in video sequence. HMM consists of two interrelated processes: (1) an underlying, unobservable Markov chain with a finite number of states, a state transition probability matrix and an initial state probability distribution and (2) a set of probability density functions associated with each state [9]. The used approach is based on the technique proposed by A. Nefian and Monsson Hayes III in [5]. This technique involves the extraction of the face features in order to detect it. Each face image of width W and height H is divided into overlapping blocks of height L and width W. The amount of overlap between consecutive blocks is P. T is the number of observations which denotes the number of blocks extracted from each face. T is generated using equation 1:

$$T = \frac{H - L}{L - P} + 1 \tag{1}$$



<u>Figure</u> 1 is an illustration of face image parameterization and blocks extractions.

Particular facial regions such as: hair, forehead, eyes, nose and mouth come in a natural order from top to bottom, even if the images are taken under small rotations in the image plane. Each of these facial regions is assigned to a state from the left to the right topology of HMM. Note that, the state structure of the face model and the non-zero transitions probabilities are shown in Figure 2.

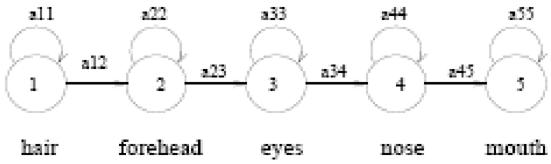


Figure 2: Left to right HMM for face recognition [5].

Two main steps are used by HMM to detect and recognize faces. Among these steps, we have training the face model and their recognition. For the training step, we use an HMM face model to represent each individual in the database. A set of five images representing different instances of the same face are used to train each HMM. In the recognition phase, the probability of the observation vector given each HMM face model is computed after extracting the observation vectors as in the training phase. Shown in Figure 3 and Figure 4, an illustration for training and recognition step with HHM. A face image t is recognized as face k if:

$$P\left(O^{(t)} \mid \lambda_{\mathrm{k}}\right) = Max_n P\left(O^{(t)} \mid \lambda_n\right) \tag{2}$$

After the face detection, the facial expression recognition system performs the mouth and the eye region feature extraction using the pixel intensity code value to recognize facial expression in images sequences.

2.2. Feature Extraction Process from Eye and Mouth Region

This work exploits the temporal intensity change of expressions in videos for facial expression recognition through the HMM. Considering the intensity scale of the different facial expressions, each person has his/her own maximal intensity of displaying a particular facial action. We combine the Mouth region intensity Code Value namely MICV [1] and the Eye region Intensity Code Value namely EICV as features for facial expression recognition.

In this section, we describe how we compute the eye and the mouth region intensity coded value (EICV/MICV). The E/MICV for eye and the mouth region which characterizes the intensity variations between blocks that corresponds respectively to the eye and the mouth region in a video frame is computed using a simple procedure that divides a mouth region into blocks and creates a code called EICV and MICV which represents the intensity difference between blocks in a frame. Eq. (3) illustrates the generation of proposed MICV feature [1]. *i* and *j* represent the i_{th} and j_{th} blocks in a frame. MICV is generated using Equation 3 [8]:

$$y\left[(i-1)25+j-\frac{i(i+1)}{2}\right]=\begin{cases}1 \text{ if } x(i)>x(j)\\ 0 \text{ Otherwise}\end{cases}$$

$$1\leq i\leq 25, 2\leq j\leq 25 \text{ and } i<j \quad (3)$$

Where *x(i), x(j)* are the average intensities of the i_{th} and j_{th} blocks respectively. To generate the MICV, for example, the frame is divided into 5 x 5 blocks to generate the feature vector. Figure 3 shows the detected mouth region and the 5 x 5 representation of mouth region.

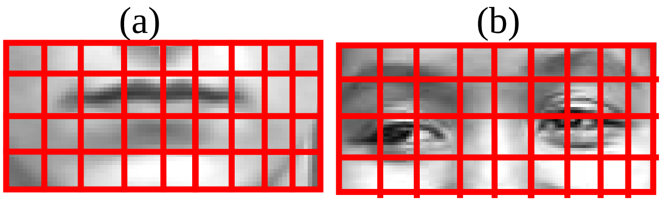


Figure 3: (a) representation of mouth region and (b) the same for eye region

To generate the MICV [1], for example, the frame is divided into 5 x 5 blocks to generate the feature vector. Fig. 3a and 3b show the detected eye and mouth region with both their representation. Each block in a frame is compared with every other block to generate EICV and MICV using "Eq. (4)". For example, if the image is divided into 5 x 5 blocks, then "Eq. (4)" generates 300 dimensional feature vectors. First element in the feature vector compares the intensity of 1st and 2nd block; second element compares the intensity of 1st and 3rd block and so on. The distance or error between the two comparison codes $p=(P_1,P_2,P_3,......,P_n)$ and $q=(q_1,q_2,q_3,........,q_n)$ can be calculated using equation 4:

$$d=\sum_{k=1}^{n}(p_k\oplus q_k) \quad (4)$$

2.3. Robust and Flexible Facial Expression Recognition

The proposed system for facial expressions recognition is using an evidential Hidden Markov Model (EvHMM) developed by E. Ramasso in [7] and first introduced by [11]. This version of HMM is based on an extension of probabilistic reasoning framework to the evidential. This new reasoning framework is very generic and powerful to develop tools to support any type of application with better management of uncertainty and imperfect data. In addition, it is possible to combine information with the careful fusion rules and operators. In this work, we proposed a new and robust approach for event recognition in videos sequences. A substantial benefit of belief functions is their versatility and efficiency in the information fusion process. Transferable Belief Model is a very suitable tool for information combination as it takes into account the nature and quality of sources to provide noisy information [13]. Another advantage of the reasoning part also lies in its ability to manage the imperfections of the data in order to estimate the best accuracy recognition system. In the related work, we noted that facial expression recognition from still image has less precision with respect to video sequence because a single image offers much less information than a sequence of images for expression recognition processing.

Feature classification is performed in the last stage of our automatic facial expression analysis system. Hidden Markov Models (HMMs) have been widely used to model the temporal behaviors of facial expressions from image sequences. This work exploits HMM to recognize facial expression. Three basic facial actions are defined (neutral, smile, eyes closed and raised eyebrows) and five emotional or facial expressions (neutral, happy, anxious, painful, and disgusted) can be recognized by the system. For each facial expression, we use an Evidential HMM for training the model and afterwards to recognize its. We define five HMMs to recognize the facial expression which are *"neutral", "happy", "disgust", "pain" , and "anxious"*. Facial expressions features such as EICV and MICV are computed in probabilistic quantity. And then, we have combined in the belief mass two main information estimated on the eye region features named (Eye Intensity Probability Value: EIPV) and the mouth region features called (Mouth intensity Probability Value: MIPV). The result of EIPV and MIPV combination design Facial Expression Code Value (FECV) is given as input to estimate Ev-HMM parameter from the learning step. The remainder of this section describes the HMM learning process and the recognition of facial expressions through two steps. These steps are implemented using the beliefs parameter input in probabilistic HTK toolkit for the expression recognition.

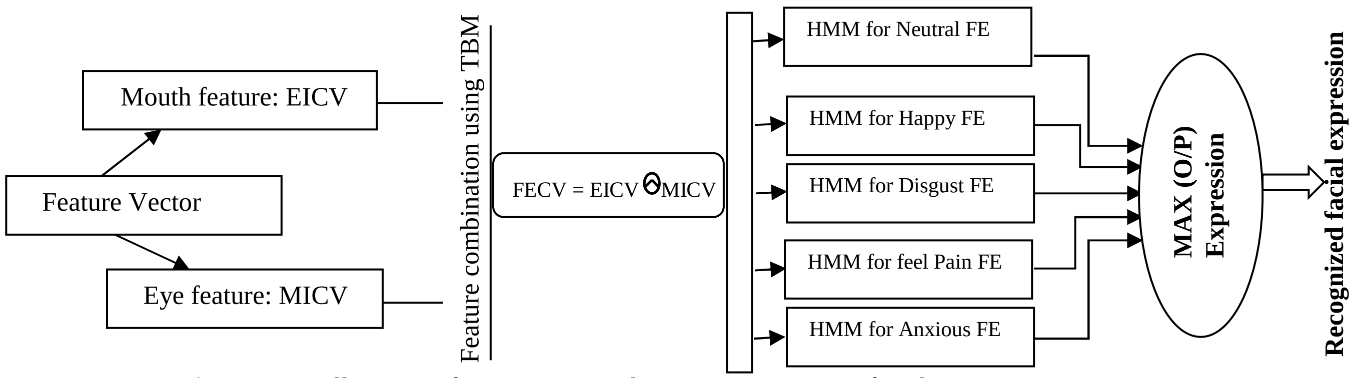


Figure 4: An illustration for Ev-HMM architecture to recognize facial expressions

2.3.1. TBM tools overview

Transferable Belief Model (TBM) is a generic formal framework [12] for the knowledge representation and information combination. This framework provides powerful tools for managing data uncertainty and imprecision. In this work, TBM is used to combine the mouth/eye features parameter of facial expression recognition in single parameter named Facial Expression Code Value (FECV). Our models use the belief mass for estimate the sensor confidence and we transform it in the Communality function before combining information. This section succinctly reviews some TBM basic notions [13].

Indeed, TBM framework provides powerful tools for managing data uncertainty and imprecision. In our work the TBM is used to propagate uncertainty of low level information over the scenario recognition process. This section succinctly reviews some TBM basic notions [14]. Several functions which are the belief masses, the Credibility *(bel : Belief)* , the Plausibility *(pl)* and the Communality *(q)* are defined in the TBM. The belief of an agent in subsets of the frame of discernment Ω_t can be represented by a basic belief assignment *(BBA)*, also called *belief mass assignment (*equation 8*)*:

$$m^{\Omega_t} : \rightarrow [0\ 1] \qquad B \mapsto m^{\Omega_t}(B) \tag{8}$$

Such as $\sum_{B \in P(\Omega)} m^{\Omega_t}(B) = 1$ and $m^{\Omega_t}(\phi) = 0$

The mass noted m^{Ω_t} is the part of belief the information source at *t* time. Moreover, the use of communalities functions makes them less cumbersome and time consuming calculations while providing near those probabilistic expressions. Accordingly, the use of this belief function is a main advantage of computational complexity for proposed recognition algorithm. In equation (9), this function is defined as:

$$q^{\Omega_t}(B) = \sum_{C \supseteq B} m^{\Omega_t}(B), \forall \mathrm{B} \subseteq \Omega_{\mathrm{t}} \tag{9}$$

2.3.2. Step 1: Evidential HMM training

For HMM training, FECV is computed after the EPIV and MIPV are extracted using respectively eye and mouth region intensity from each frame in the video sequence and is given as input to estimate the parameters of Ev-HMM. Learning of model parameters consists in defining a technique for estimating and automatic adjustment of parameter by exploiting the features of training data. We propose to use a Credal version of HMM algorithm proposed in my previous paper in order to handle the spatial and temporal variability and also the uncertainty existing over the machine learning task. To this end, regrouping components into states is made automatically by maximizing likelihood, and a relevant regrouping implies a better recognition of states. Given observations sets how to adjust the HMM parameters to maximize the training set likelihood? For this, we have used three levels for Ev-HMM learning step. Nevertheless, it should be noted that the complexity of the Baum-Welch algorithm in its credal version that we present in [2]. This is due to the beliefs functions that do not have the same mathematical properties those probabilities and over, beliefs functions are defined on large space discernment. Three parameters are usually learned during the Ev-HHMM training step. Indeed, two key levels passing by an initialization phase helps to describe Baum-Welch in credal version used for learning:

1. **Initialization level**: Ev-HInit does initialization. It computes an initial set of parameter values using Viterbi alignment to segment the training observations and then recomputed the parameters by pooling the vectors in each segment.

2. **Level 1:** To determine the parameters of Ev-HMM, the output of Ev-HInit is fed as input **&**into Ev-HRest. The models are re-estimated using Baum-Welch re-estimation.

3. **Level 2:** Testing the data against the model built.

The HMM classification scheme used in the present approach is shown in Fig. 4. Initially, separate HMMs are used for each expression. FECV is fed as input to the Ev-HMM. Finally, the maximum output obtained is considered as the output expression.

2,3.3. Step 2: Facial Expressions Recognition by Ev-HMM

This step concerns the test of the data against the model built. The Ev-HMM classification scheme used in thiq approach is shown in Fig. 4. Initially, separate Ev-HMMs are used for each expression. FECV is fed as input into the Ev-HMM. Finally, the maximum output obtained is considered as the output expression. Upon completion of learning step, the properly so called recognition stage is carried out. For this purpose, we use credal forward and backward propagation [2]. The propagations processes follow the same traditional patterns as those existing in the probabilistic framework [2,4]. In the case of credal forward propagation, it is done in three steps which are: initialization, induction and end step. Moreover, Credal Backward propagation makes the complete estimation of HMM parameters requires the computation of three auxiliary variables which are: the backward variable β and the smoothing variables γ and ξ. In fact, a similar process can be used in Ev-HMM [21] for the backward propagation to generate a backward variable $q_{\beta}^{\Omega_t}(S_j)$ in the prediction and melting process which is estimated with equation 5:

$$q_{\beta}^{\Omega_t}(S_i) = \sum \left(m_{\beta}^{\Omega_t} \circledcirc m_b^{\Omega_t}[O_t]\right)(S_j) \times q_{\alpha}^{\Omega_t}[S_j](S_j) \tag{5}$$

$$q_{\beta}^{\Omega_t}(S_i) = \sum \left(m_{\beta}^{\Omega_t} \circledcirc m_b^{\Omega_t}[O_t]\right)(S_j) \times q_{\alpha}^{\Omega_t}[S_j](S_j) \tag{6}$$

$$\forall S_i \subseteq \Omega_t, q_{\beta}^{\Omega_t}(S_i) = \sum \left(m_{\beta}^{\Omega_t} \circledcirc m_b^{\Omega_t}[O_t]\right)(S_j) \times q_{\alpha}^{\Omega_t}[S_j](S_j) \text{ in induction phase} \tag{7}$$

3. Applying Method to Recognize Facial Expression in Medical Video

In this section, we present on one hand, an appliance of evidential Markov model for facial expression recognition and on the other hand, the experimental results on real-world facial expression dataset. In addition, we described the used datasets and presented the experimental results of even the performance analysis of the proposed approach compared it to other existing methods. An experimental study conducted in two datasets (Cohn-Kanade [14] AU code facial expression database and our database) shows good performance of our proposed method in term of recognition rate precision and its accuracy. Our Algorithms have been implemented using Matlab, C/C++ using OpenCV library).

3.1. Tested Data Setup

In order to test the algorithms described in the previous sections we use two different databases, a database collected by us and the Cohn-Kanade [14] AU code facial expression database. The first used benchmark (FACS) which is Cohn-Kanade AU-Coded Facial Expression Database is for research in automatic facial image analysis, synthesis and for perceptual studies. We used the second version of the Cohn-Kanade to test our algorithm. Facial behavior of 210 adults was recorded using two hardware synchronized Panasonic AG-7500 cameras. Participants were 18 to 50 years of age, 69% female, 81%, Euro-American, 13% Afro-American, and 6% other groups. Image sequences for frontal views and 30-degree views were digitized into either 640x490 or 640x480 pixel arrays with 8- bit gray-scale or 24-bit color values. Full details of this database are given in [14]. The second test database is ours. The data collection method is described in detail in [3], our database has been collected from the experimental video-surveillance system that we installed in the cardiology department at the hospital (have collected roughly 47 videos sequences for three activities with 1500 frames/sequences. An observation sequence is recorded every one and a half second from the 25fps video. The duration of the video sequences is 300 seconds with an average length of circa 90 seconds. In this database, we have the subjects that were instructed to display facial expressions corresponding to the five types of emotions such as *"neutral"*, *"happy"*, *" disgust"*, *"pain"* , and *"anxious"*. Four basic actions (***neutral, smile, eyes closed and raised eyebrows***) detected over the face feature extraction step are used through like input data of the Evidential HMM to recognize these facial expressions.

3.2. Experiments Results 1: *Using Cohn-Kanade AU database*

All the tests of the algorithms are performed on a set of five persons, each one displaying five sequences of each of the five emotions, and always coming back or not to a neutral state between each emotion sequence. The sampling rate of the video sequence was 30 Hz, and a typical emotion sequence is about 150 samples long (5s). Figure 5, shows one frame of each emotion for each subject. We used the sequences from a set as test sequences and the remaining sequences were used as training sequences. In this case, we performed person dependent experiments, in which part of the data for each subject was used as training data, and another part as test data. Table 1 show the recognition rate of the test for each HMM version. Note that the results obtained with this database are much better than the ones obtained with our database. This is because in this case we have more training data. Furthermore, it is observed that among the five expressions "*happy*" expression is well (98% recognition rate) recognized than the others (between 70% and 85% recognition rate). It can also be seen that the evidential HMM with temporal constraints, achieves the best recognition rate (and improves it in some cases) compared to the other used version HMM, even though the input is segmented as continuous video. The other expressions are greatly confused with one another other. See below an illustration results in Table I.

See in following Figure 5, the examples of images from the video sequences used in the experiment.

Figure 5: Used data of Cohn-Kanade AU database

Facial expressions/HMM Model	Classic HMM	Temporal HMM	Hierarchical HMM	Evidential HMM
Neutral	70,00	70,00	72,00	80,00
Happy	80,00	85,00	85,00	98,00
Disgust	60,00	62,00	63,00	70,00
Surprise	70,00	80,00	80,00	85,00

Table I: Facial Expression recognition rate for Cohn-Kanade AU database (average in %)

3.3. Experiments Results 2: *Using Medical videos database*

Our experimental data were collected in an open recording scenario, where the patient was asked to display the expression corresponding to the emotion being induced: This is a simulation process for generating facial expressions in medical context. Although we are aware that this assumption does not take into account all the constraints related to the real conditions of facial expressions data collection, we think that, the experimental result achieved shows involved significantly the technological progress. For complex and highly sensitive applications such as patient monitoring in medical UCIs, power, robustness and efficiency of the proposed model stands out and improves very significant way the performance of the expressions recognition system facial. The specific facial expressions recognition rate to the medical context such as feel the pain and the patient is in anxious condition depends on the performance of the facial feature extraction system for the detection of facial expressions basic such as smile, eyes closed, eyebrows raised and finally neutral. In average, the best results of facial expression recognition were obtained using Ev-HMM. The temporal layer assumption gives a significant improvement in recognition rate comparing with standard probabilistic HMM. Find in Table 2 & 3, the results reporting the facial expression recognition rate reached depending on the various kinds of HMM we tested. In this used case of Ev-HMM, *"Happy"* was detected with over 96% accuracy and Disgust with over 83% accuracy. Whereas, the patient's behavior like fells the pain and anxious state are recognized at respectively 78 % and 70%.

See in following Figure 6, the examples of images from the medical video sequences used in the experiment.

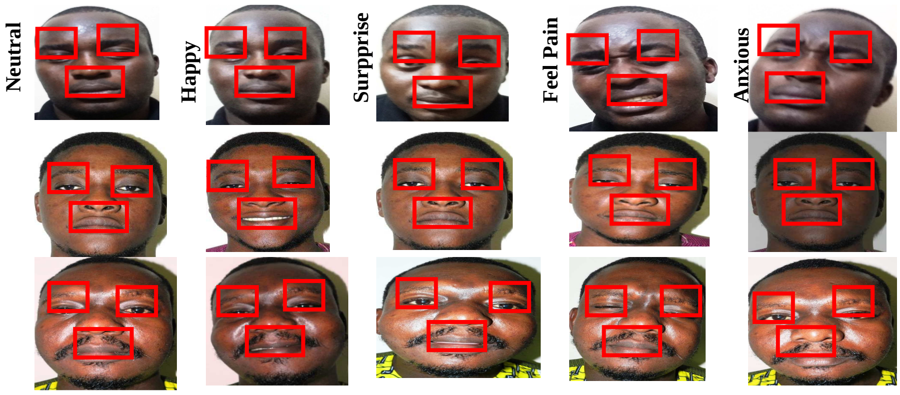


Figure 6: Our used data gathered from experiment video surveillance system in UCIs.

Facial expressions/HMM Model	**Classic HMM**	**Temporal HMM**	**Hierarchical HMM**	**Evidential HMM**
Neutral	70,00	75,00	78,00	80,00
Happy	76,00	80,00	80,00	85,00
Disgust	65,00	70,00	72,00	96,00

Table II: Facial Expression recognition rate for our test database (average in %)

Facial expressions/HMM Model	**Classic HMM**	**Temporal HMM**	**Hierarchical HMM**	**Evidential HMM**
Neutral	52,00	55,00	55,00	80,00
Happy	60,00	80,00	80,00	96,00
Disgust	53,00	70,00	70,00	83,00
The patient feels pain	54,00	55,00	55,00	78,00
The patient Anxiety	50,00	52,00	55,00	70,00

Table III: Facial Expression recognition rate for our test database (average in %)

5. Conclusion

We have developed in this work, a computer vision system that automatically recognizes a series of complex facial expressions. Our recognition system applied to psychological research in medical field. In the first instance, the proposed approach has been tested on a generic [AUBd] database of facial expression to assess the system is performance and efficiency .More specifically, the proposed system was used to recognize the patient's specific behaviors closely linked to his facial expressions and emotions (resentment pain and mental state of anguish) in cardiological ICUs. A Robust and powerful approach for automatic facial recognition expression using HMM in belief framework is presented. The proposed work is able to detect human faces over extracting face features using HMM tool by segmenting face from the real time video. Among the facials expressions, *happy* and *disgust* expressions has been recognized with an accuracy of 96% but expressions *neutral* and *disgust* cannot be distinguished well. Thank to our method, because it provides better rate recognition with complex expressions in a medical environment such as the issue of pain and patient anxious are not easy to recognize. Nevertheless, our system has allowed us to recognize these two expressions with a rate of about 83% on average. Hence the future work aims to apply the feature extracted in this work to the forehead and noise region and also considering more number of expressions. In addition, we think to take into account a generic maximal intensity for all people because that is the lack in current model, each person has his/her own maximal intensity of displaying a particular facial action. This work is just another step on the way toward achieving the goal of building more effective medical computers-assisted that can help us better analyzing physiological states such as heart beat and skin conductivity of patient in critical care.

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