

Full Length Research Paper

Hidden Markov model/Gaussian mixture models (HMM/GMM) based voice command system: A way to improve the control of remotely operated robot arm TR45

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A speech control system for a didactic manipulator arm TR45 is designed as an agent in a tele-manipulator system command. Robust Hidden Markov Model (HMM) and Gaussian Mixture models (GMM) are applied in spotted words recognition system with Cepstral coefficients with energy and differentials as features. The HMM and GMM are used independently in automatic speech recognition agent to detect spotted words and recognize them. A decision block will generate the appropriate command and send it to a parallel port of the Personal Computer (PC). To implement the approach on a real-time application, a PC parallel port interface was designed to control the movement of robot motors using a wireless communication component. The user can control the movements of robot arm using a normal speech containing spotted words.

Key words: Human-machine interaction, hidden Markov model, Gaussian mixture models, artificial intelligence, automatic guided vehicle, voice command, robot arm and robotics.

INTRODUCTION

Manipulator robots are used in industry to reduce or eliminate the need for humans to perform tasks in dangerous environments. Examples of it include space exploration, mining, and toxic waste cleanup. However, the motion of articulated robot arms differs from the motion of the human arm. While robot joints have fewer degrees of freedom, they can move through greater angles. For example, the elbow of an articulated robot can bend up or down whereas a person can only bend their elbow in one direction with respect to the straight arm position (Beritelli et al., 1998; Bererton and Khosla, 2001). There have been many research projects dealing with robot control and tele-operation of arm manipulators, among these projects, there are some projects that build intelligent systems (Kwee, 1997; Buhler et al., 1994;

Ibrahim et al., 2010; www.ieeexplore.ieee.org/iel5/5398724/5404079/05404143.pdf?..). Since we have seen human-like robots in science fiction movies such as in "I ROBOT" movie, making intelligent robots or intelligent systems became an obsession within the research group.

In addition, speech or voice command as human-robot interface has a key role in many application fields and various studies made in the last few years have given good results in both research and commercial applications (Bererton and Khosla, 2001; Rao et al., 1998;

www.alzaytoonah.edu.jo/ICIT2009/documents/accepte%20papers.pdf;

www.ieeexplore.ieee.org/iel5/5398724/5404079/05404143.pdf?.. ; Yussouf et al., 2005) just for speech recognition systems. In this paper, we present a new approach to solve the problem of the recognition of spotted words within a phrase, using statistical approaches based on

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HMM and GMM (Gu and Rose, 2001; Rabiner, 1989). By combining the two methods, the system achieves considerable improvement in the recognition phase, thus facilitating the final decision and reducing the number of errors in decision taken by the voice command guided system.

Speech recognition systems constitute the focus of a large research effort in Artificial Intelligence (AI), which has led to a large number of new theories and new techniques. However, it is only recently that the field of robot and Automatic Guided Vehicle (AGV) navigation has started to import some of the existing techniques developed in AI for dealing with uncertain information. HMM is a robust technique developed and applied in pattern recognition. Very interesting results were obtained in isolated words speaker independent recognition system, especially in limited vocabulary. However, the rate of recognition is lower in continuous speaking system. The GMM is also a statistical model that has been used in speaker recognition and in isolated word recognition systems. These two techniques HMM and GMM were experimented independently and then combined in order to increase the recognition rate. The approach proposed here in this paper is to design a system that gets specific words within a large or small phrase, process the selected words (Spots) and then execute an order (Djemili et al., 2004; Rabiner, 1989; www.ieeexplore.ieee.org/jel5/5398724/5404079/05404143.pdf?..). As an application of this approach, a set of four reduction motors were activated via a wireless designed system installed on a Personal Computer (PC) parallel port interface. The application uses a set of twelve commands in Arabic words, divided in two subsets one subset contains the names of main parts of a robot arm (arm, fore-arm, wrist (hand), and gripper), the second subset contains the actions that can be taken by one of the parts in subset one (left, right, up, down, stop, open and close). A specific word like "yade" which means arm is also used at the beginning of the phrase as a "password". Voice command needs the recognition of spotted words from a limited vocabulary used in AGV system (Ferrer et al., 2000; Heck, 1997) and in manipulator arm control (Rodriguez et al., 2003).

APPLICATION DESCRIPTION

Our used application is based on the voice command for a set of four reduction motors. It therefore involves the recognition of spotted words from a limited vocabulary used to recognise the part and the action of a robot arm.

The vocabulary is limited to twelve words divided into two subsets: object name subset necessary to select the part of the robot arm to move and command subset necessary to control the movement of the arm example

like: turn left, turn right and stop for the base (shoulder), Open close and stop for the gripper. The number of words in the vocabulary was kept to a minimum both to make the application simpler and easier for the user.

The user selects the robot arm part by its name then gives the movement order on a microphone, connected to sound card of the PC. The user can give the order in a natural language phrase as example: "Yade, gripper open execute". A speech recognition agent based on HMM technique detects the spotted words within the phrase, recognises the main word "Yade" which is used as a keyword in the phrase, it recognises the spotted words, then the system will generate a byte where the four most significant bits represent a code for the part of the robot arm and the four less significant bits represent the action to be taken by the robot arm. Finally, the byte is sent to the parallel port of the PC and then it is transmitted to the robots through a wireless transmission system.

The application is first simulated on PC. It includes three phases: the training phase, where a reference pattern file is created, the recognition phase where the decision to generate an accurate action is taken and the appropriate code generation phase, where the system generates a code of 8 bits on parallel port. In this code, four higher bits are used to codify the object names and four lower bits are used to codify the actions. The action is shown in real-time on parallel port interface card that includes a set of four stepper motors to show what command is taken and the radio frequency emitter.

THE SPEECH RECOGNITION AGENT

The speech recognition agent is based on HMM. In this paragraph, a brief definition of HMM is presented and speech processing main blocks are explained. However, a pre-requisite phase is necessary to process a data base composed of twelve vocabulary words repeated twenty times by fifty persons (Twenty five male and twenty five female). So, before starting in the creation of parameters, 50*20*12 "wav" files are recorded in a repository. Files from 35 speakers are saved on DB1 to be used for training and files from 15 speakers are used for tests and then saved in DB2, these tests are done off-line.

In the training phase, each utterance (saved wav file) is converted to a Cepstral domain (MFCC features, energy, and first and second order deltas) which constitutes an observation sequence for the estimation of the HMM parameters associated to the respective word. The estimation is performed by optimisation of the likelihood of the training vectors corresponding to each word in the vocabulary. This optimisation is carried by the Baum-Welch algorithm (Rabiner, 1989;

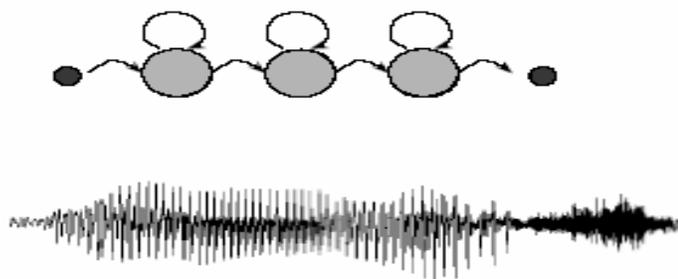


Figure 1. Presentation of left-right (Bakis) HMM.

Ibrahim et al., 2010).

HMM MODEL BASICS

A HMM is a type of stochastic model appropriate for non stationary stochastic sequences, with statistical properties that undergo distinct random transitions among a set of different stationary processes. In other words, the HMM models a sequence of observations as a piecewise stationary process. Over the past years, HMM have been widely applied in several models like pattern (Djemili et al., 2004), or speech recognition (Djemili et al., 2004; Ferrer et al., 2000). The HMMs are suitable for the classification from one or two dimensional signals and can be used when the information is incomplete or uncertain. To use HMM, we need a training phase and a test phase. For the training phase, we usually work with the Baum-Welch algorithm to estimate the parameters (Π, A, B) for the HMM (Rabiner, 1989; Ferrer et al., 2000). This method is based on the maximum likelihood criterion. To compute the most probable state sequence, the Viterbi algorithm is the most suitable.

The HMM model is basically stochastic finite state automaton which generates an observation string, that is, the sequence of observation vectors, $O = O_1, \dots, O_t, \dots, O_T$. Thus, HMM model consists of a number of N states $S = \{S_i\}$ and of the observation string produced as a result of emitting a vector O_t for each successive transitions from one state S_i to a state S_j . O_t is d dimension and in the discrete case takes its values in a library of M symbols.

The state transition probability distribution between state S_i to S_j is $A = \{a_{ij}\}$, and the observation probability distribution of emitting any vector O_t at state S_j is given by $B = \{b_j(O_t)\}$. The probability distribution of initial state is $\Pi = \{\pi_j\}$.

$$a_{ij} = P(q_{t+1} = S_j / q_t = S_i) \tag{1}$$

$$B = \{b_j(O_t)\} \tag{2}$$

$$\pi_i = P(q_0 = S_i) \tag{3}$$

Given an observation O and a HMM model $\lambda = (A, B, \Pi)$, the probability of the observed sequence by the forward-backward procedure $P(O/\lambda)$ can be computed (Kwee, 1997). Consequently, the forward variable is defined as the probability of the partial observation sequence O_1, O_2, \dots, O_t (until time t) and the state S at

time t , with the model λ as $\alpha(i)$. The backward variable is defined as the probability of the partial observation sequence from $t+1$ to the end, given state S at time t and the model λ as $\beta(i)$. The probability of the observation sequence is computed as follow:

$$P(O/\lambda) = \sum_{i=1}^N \alpha_i(i) * \beta_i(i) = \sum_{i=1}^N \alpha_T(i) \tag{4}$$

and the probability of being in state l at time t (given the observation sequence O and the model λ) is computed as follows:

$$\pi_i = P(q_0 = S_i) \tag{5}$$

The flowchart of a connected HMM is an HMM with all the states linked altogether (every state can be reached from any state). The Bakis HMM is left to right transition HMM with a matrix transition defined as shown in Figure 1.

GMM MODEL BASICS

The GMM can be viewed as a hybrid model between parametric and non- parametric density models as shown in Figure 2. Like a parametric model, it has structure and parameters that control the behavior of density in known ways. Like non-parametric model it has many degrees of freedom to allow arbitrary density modeling. The GMM density is defined as weighted sum of Gaussian densities given by Equation 6 as follows:

$$P_{G.M}(x) = \sum W_m g(x, m_m, C_m) \tag{6}$$

Here m is the Gaussian component ($m=1 \dots M$), and M is the total number of Gaussian components. W_m are the component probabilities ($\sum w_m = 1$), also called weights. We consider K -dimensional densities, so the argument is a vector $x = (x_1, \dots, x_K)^T$. The component probability

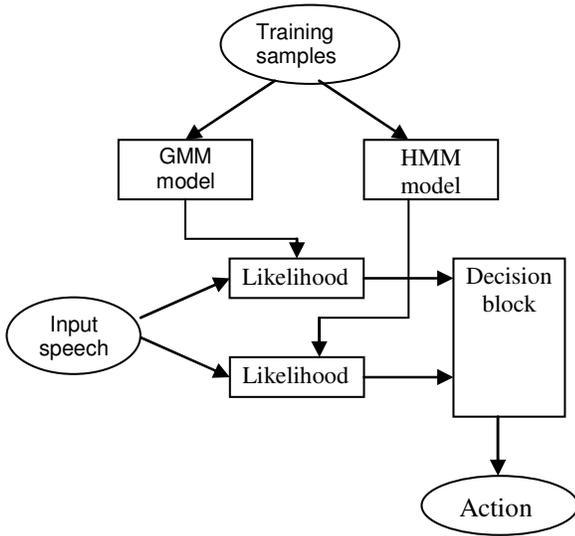


Figure 2. Speech recognition agent based on HMM/GMM model.

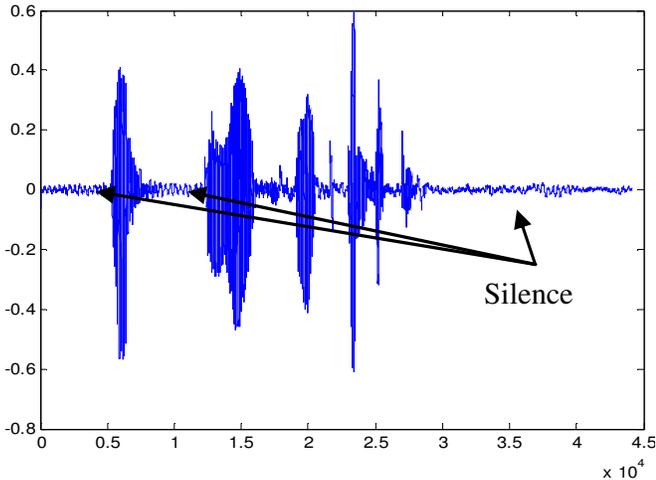


Figure 3. Phrase test “yade diraa fawk tabek” and Silence at the beginning and at the end.

density function (pdf), $g(x, \mu_m, C_m)$, is a K-dimensional Gaussian probability density function (pdf) given in Equation 7 as follows:

$$g(x, \mu_m, C_m) = \frac{1}{(2\pi)^{k/2} |C_m|^{1/2}} e^{-1/2(x-\mu_m)^T C_m^{-1}(x-\mu_m)} \quad (7)$$

Where μ_m is the mean vector, and C_m is the covariance matrix. Now, a Gaussian mixture model probability density function is completely defined by a parameter list given by $\theta = \{w_1, \mu_1, C_1 \dots w_1, \mu_1, C_1\}_m, m=1 \dots M$.

Organizing the data for input to the GMM is important since the components of GMM play a vital role in making the word models. For this purpose, we use K-means clustering technique to break the data into 256 cluster centroids. These centroids are then grouped into sets of 32 and then passed into each component of GMM. As a result, we obtain a set of 8 components of GMM. Once the component inputs are decided, the GMM modelling can be implemented as (Figure 3).

EM ALGORITHM

The expectation maximization (EM) algorithm is an iterative method for calculating maximum likelihood distribution parameter estimates from incomplete data (elements missing in feature vectors). The EM update equations are used which gives a procedure to iteratively maximize the log-likelihood of the training data given the model. The EM algorithm is a two step process:

$$y(m, t) = \frac{w_m^i g(x_t, \mu_m^i, C_m^i)}{\sum_{m=1 \dots M} w_j^i g(x_t, \mu_j^i, C_j^i)} \quad (8)$$

Estimation step in which current iteration values of the mixture are utilized to determine the values for the next iteration as given in Equation 8.

Maximization step in which the predicted values are then maximized to obtain the real values for the next iteration as given in Equations 9, 10 and 11.

$$\mu_m^{i+1} = \frac{\sum_{t=1 \dots T} y_{m,t} X_t}{\sum_{t=1 \dots T} y_{m,t}} \quad (9)$$

$$W_m^{i+1} = \sum_{t=1 \dots T} y_{m,t} \quad (10)$$

$$\lambda_{m,j}^{i+1} = \frac{\sum_{t=1 \dots T} y_{m,t} (x_{t,j} - \mu_{m,j}^{i+1})^2}{\sum_{t=1 \dots T} y_{m,t}} \quad (11)$$

EM algorithm is well known and highly appreciated for its numerical stabilities under threshold values of λ_{min} . Using the final re-estimated w, μ and C , the value of L_{GMM} is calculated with respect to all the word models available with the recognition engine as shown in Equation 12

$$L_{GMM} = \frac{1}{T} \sum_{t=1 \dots T} \log P_{GM}(X_t) \quad (12)$$

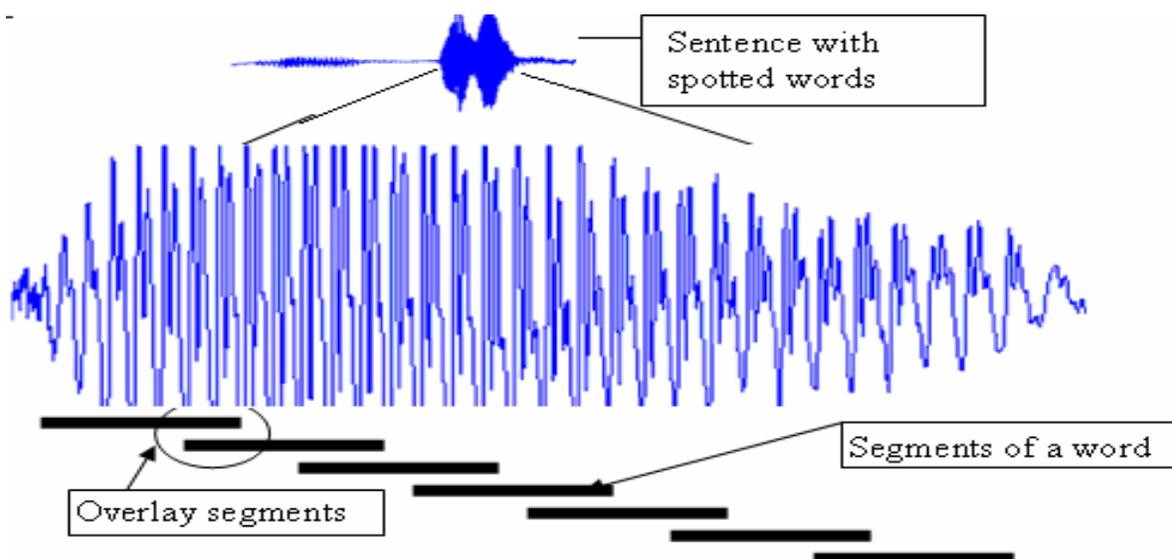


Figure 4. Windowing diagram.

HMM/GMM MODEL

The HMM/GMM hybrid model has the ability to find the joint maximum probability among all possible reference words W given the observation sequence O . In real case, the combination of the GMMs and the HMMs with a weighted coefficient may be a good scheme because of the difference in training methods. The i th word independent GMM produces likelihood $LiGMM$, $i = 1, 2, \dots, W$, where W is the number of words. The i th word independent HMM also produces likelihood $LiHMM$, $i = 1, 2, \dots, W$. All these likelihood values are passed to the likelihood decision block, where they are transformed into the new combined likelihood $L'(W)$:

$$L'(W) = (1 - x(W))LiGMM + x(W)LiHMM \quad (13)$$

Where $x(W)$ denotes a weighting coefficient.

The value of x is calculated during training of the Hybrid model. In Hybrid Testing, the subset of training data is used and its HMM and GMM likelihood values are calculated which combined using weighing coefficient. Static values of weighted coefficient are also used in order to get higher recognition rate. In that case the conception of 12 HMM models one per vocabulary word and 12 GMM models, one for each word. The resulting of both models is taken by the decision block.

SPEECH PROCESSING PHASE

Once the phrase is acquired through a microphone and

the PC sound card, the samples are stored in a wav file. Then the speech processing phase is activated. During this phase the signal (samples) goes through different steps: pre-emphasis, frame-blocking, windowing, feature extraction and Mel-Filter Cepstral Coefficients (MFCC) analysis.

Pre-emphasis step

In general, the digitized speech waveform has a high dynamic range. In order to reduce this range, pre-emphasis is applied. By pre-emphasis [1], we imply the application of a high pass filter, which is usually a first-order FIR of the form $H(z) = 1 - a \times z^{-1}$. The pre-emphasis is implemented as a fixed-coefficient filter or as an adaptive one, where the coefficient a is adjusted with time according to the autocorrelation values of the speech. The pre-emphasis block has the effect of spectral flattening which renders the signal less susceptible to finite precision effects (such as overflow and underflow) in any subsequent processing of the signal. The selected value for a in our work is 0.9375.

Frame blocking

Since the vocal tract moves mechanically slowly, speech can be assumed to be a random process with slowly varying properties. Hence, the speech is divided into overlapping frames of 20 ms every 10 ms. The speech signal is assumed to be stationary over each frame and this property will prove useful in the following steps.

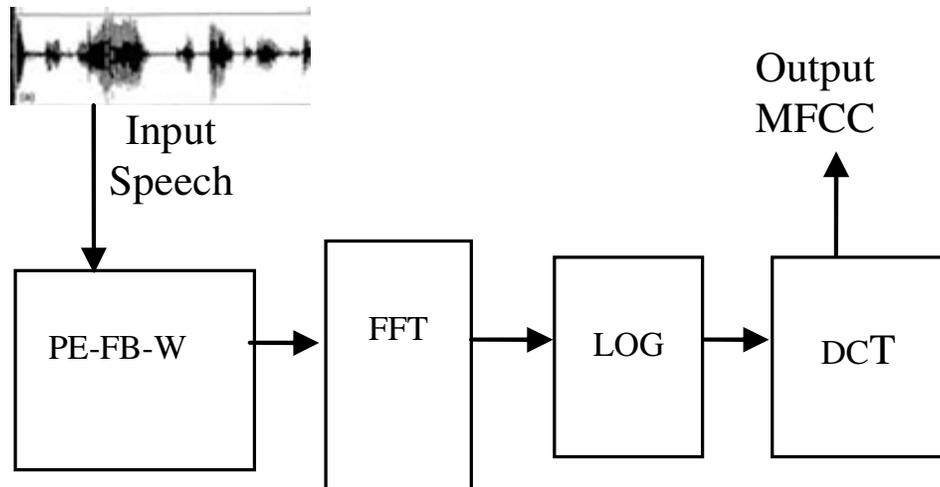


Figure 5. MFCC block diagram.

Windowing

To minimize the discontinuity of a signal at the beginning and the end of each frame, we window each frames. The windowing tapers the signal to zero at the beginning and end of each frame. A typical window is the Hamming window of the form:

$$W(n) = 0.54 - 0.46 \cos\left(\frac{2\pi n}{N-1}\right) \quad 0 \leq n \leq N-1 \quad (14)$$

Feature extraction

In this step, speech signal is converted into stream of feature vectors coefficients which contain only that information about given utterance that is important for its correct recognition. An important property of feature extraction is the suppression of information irrelevant for correct classification, such as information about speaker (e.g. fundamental frequency) and information about transmission channel (e.g. characteristic of a microphone). The feature measurements of speech signals are typically extracted using one of the following spectral analysis techniques: MFCC Mel frequency filter bank analyzer, LPC analysis or discrete fourier transform analysis. Currently the most popular features are Mel frequency Cepstral coefficients MFCC (Rabiner, 1989).

MFCC analysis

The MFCC are extracted from the speech signal as shown in Figure 4. The speech signal is pre-emphasized, framed and then windowed, usually with a Hamming window. Mel-spaced filter banks are then utilized to get

the Mel spectrum. The natural logarithm is then taken to transform into the cepstral domain and the discrete cosine transform is finally computed to get the MFCCs as shown in the block diagram of Figure 5.

$$C_k = \sum_{i=1}^N \log(E_i) * \cos\left[\frac{\pi k(i-1/2)}{N}\right] \quad (15)$$

Where the acronyms signify:

- PE-FB-W: Pre-Emphasis, Frame Blocking and windowing.
- FFT: Fast Fourier Transform
- LOG: Natural Logarithm
- DCT: Discrete Cosine Transform

PARALLEL INTERFACE CIRCUIT

The speech recognition agent based on HMM will detect words, and process each word. Depending on the probability of recognition of the object name and the command word a code is transmitted to the parallel port of the PC. The vocabulary to be recognized by the system and their meanings are listed as in Table 1. It is obvious that within these words, some are object names and other are command names. The code to be transmitted is composed of 8 bits, four bits most significant bits are used to code the object name and the four least significant bits are used to code the command to be executed by the selected object. Example: "yade diraa fawk tabek".

A parallel port interface was designed to display the real-time commands. It is based on the following TTL IC (integrated circuits): a 74LS245 buffer, a microcontroller PIC16F84 and a radio frequency transmitter from RADIO

Table 1. Meaning of the vocabulary voice commands, assigned code and controlled motor.

1) Yade (1)	Name of the manipulator (keyword)
2) Diraa (2)	Upper limb motor (M1)
3) Saad (3)	Limb motor (M2)
4) Meassam(4)	Wrist (hand) motor (M3)
5) Mikbath(5)	Gripper motor (M4)
6) Yamine (1)	Left turn (M0)
7) Yassar (2)	Right turn (M0)
8) Fawk (3)	Up movement M1, M2 and M3
9) Tahta (4)	Down movement M1, M2 and M3
10) Iftah (5)	Open Grip, action on M4
11) Ighlak (6)	Close grip, action on M4
12) Kif (7)	Stop the movement, stops M0,M1, M2, M3r or M4

METRIX TX433-10 (modulation frequency 433 Mhz and transmission rate 10 Kbs) (Table 1), Data Sheet PIC16F876 (2001).

TR45 MANIPULATOR ARM DESCRIPTION AND INTERFACE

As in Figure 6.b and 6.c, the structure of the mechanical hardware and the computer board of the robot arm in this paper is similar to MANUS (Kwee, 1997; Buhler et al., 1994). However, since the robot arm needs to perform simpler tasks than those in (Heck, 1997). do. The robot arm is composed of four feedback controlled movements for the elements: base, upper-limb, limb and wrest the movement command is realised by a moto-reductor block (1/500) powered by +12 and - 12 volts. The copy of voltage is given by a linear rotator potentiometer fixed on the moto-reductor block and powered by +10 and -10 volts.

One open loop controlled movement, for the gripper, with the same type of command. Displacement Characteristics is given by the following angle values:

Base : 290°
 Upper limb: 108°
 Lim : 280°
 Wrist : 290°
 Gripper: 100°

The computer board of the robot arm consists of a PIC16F876, with 8K-instruction Electrically Programmable Read Only Memory (EEPROM), three timers and 3 ports (Larson, 1999), four power circuits to drive the moto-reductors and one H bridges driver using BD134 and BD133 transistors for DC motor to control the

gripper, a RF receiver module from RADIOMETRIX which is the SILRX-433-10 (modulation frequency 433 MHz and transmission rate is 10 Kbs) [16 as shown in Figure 6b.

Each motor in the robot arm performs the corresponding task to a received command (example: "yamin", "kif" or Fawk") as in Table 1. Commands and their corresponding tasks in autonomous robots may be changed in order to enhance or change the application. In the recognition phase, the speech recognition agent gets the sentence to be processed, treats the spotted words, then takes a decision by setting the corresponding bit on the parallel port data register and hence the corresponding LED is on. The code is also transmitted in serial mode to the TXM-433-10, (Yamano et al., 2005).

EXPERIMENTS ON THE SYSTEM

The speech recognition agent is tested within the laboratory of L.A.S.A, were two different conditions to be tested are runes: off line, by using DB2 and on real-time. There are three types of testes: HMM and GMM models then the HMM/GMM model is tested on-line and in real-time.

The results are presented in Figure 7 After testing the recognition of command and object words 100 times in the following conditions: (a) off-line witch means test words are selected from DB1 (b) On real-time witch means some users will command the system in real-time . The results are shown in Figures 7a and b. it is obvious that the real-time test results are lower compared to that of off-line tests, this is mainly due to environment and material conditions changes.

DISCUSSION

The recognition of spotted words from a limited vocabulary in the presence of background noise was used in this paper. The application is speaker-independent. Therefore, it does not need a training phase for each user. It should, however, be pointed out that this condition does not depend on the overall approach but only on the method with which the reference patterns were chosen. So, by leaving the approach unaltered and choosing the reference patterns appropriately (based on speakers), this application can be made speaker-dependent.

The effect of the environment is also taken into consideration and here the results on the HMM/GMM model just by changing the microphone, we notice that with the microphone Mic1 used in recording the data base we get better rate than using a new microphone Mic2. The HMM based model gives better results than GMM independently, by combining GMM and HMM and using as features MFCC and differentials we increased the recognition rate. The application is speaker independent. However, by computing parameters based on speakers' pronunciation the system can be speaker dependant.

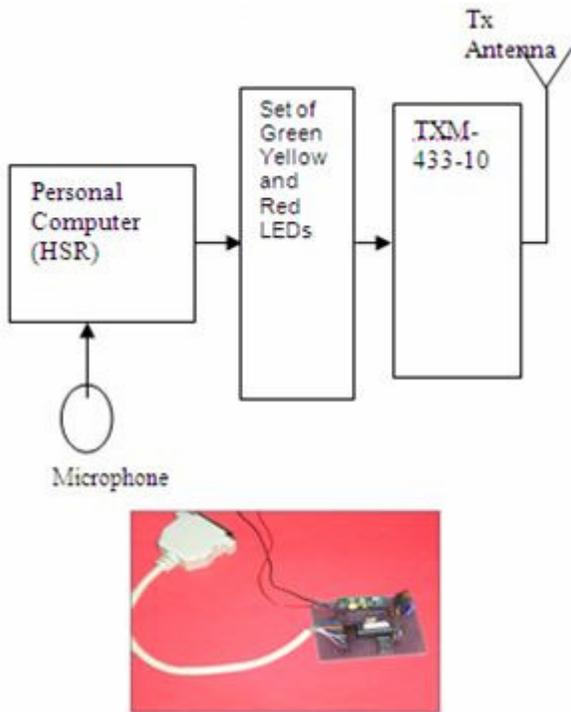


Figure 6a. Parallel interface circuit and a photo of the designed card.

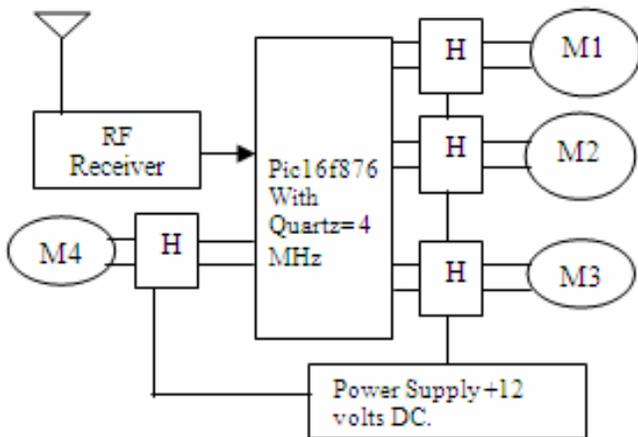


Figure 6b. Robot arm block diagram (Computer board and motors).

CONCLUSION AND FUTURE WORKS

A voice command system for robot arm is proposed and implemented in this paper based on a hybrid model HMM/GMM for spotted words. The results of the tests shows that a better recognition rate can be achieved using hybrid techniques and especially if the phonemes

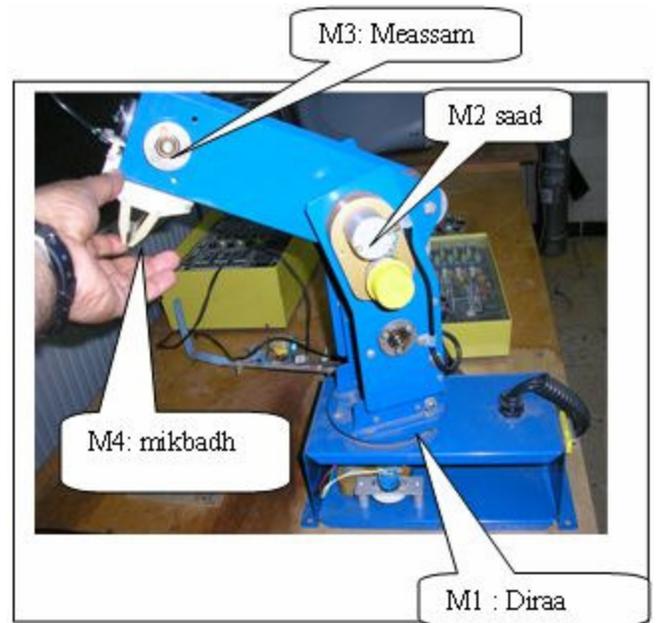


Figure 6c. Overview of the robot arm and parallel interface.

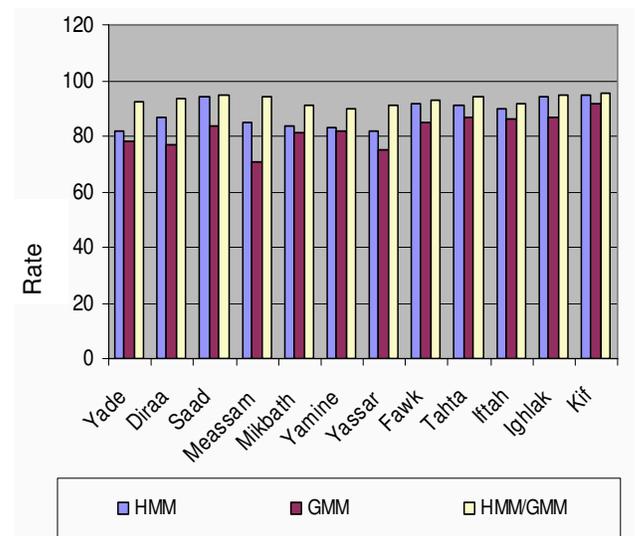


Figure 7a. HMM, GMM and HMM/GMM models results, off-line tests.

of the selected word for voice command are quite different. The effect of the used microphone for tests is proved in the results presented in Figure 7c. However, a good position of the microphone and additional filtering may enhance the recognition rate.

Spotted words detection is based on speech detection then processing of the detected. Once the parameters were computed, the idea can be implemented easily

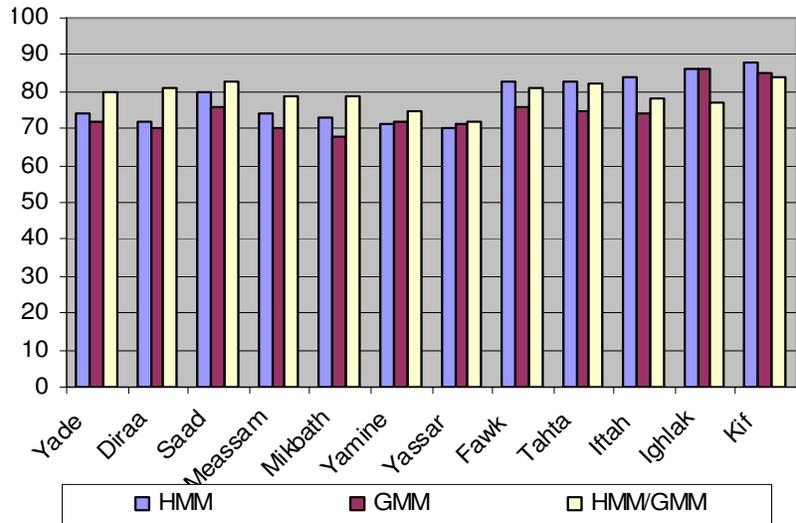


Figure 7b. HMM, GMM and HMM/GMM models results, on real-time tests.

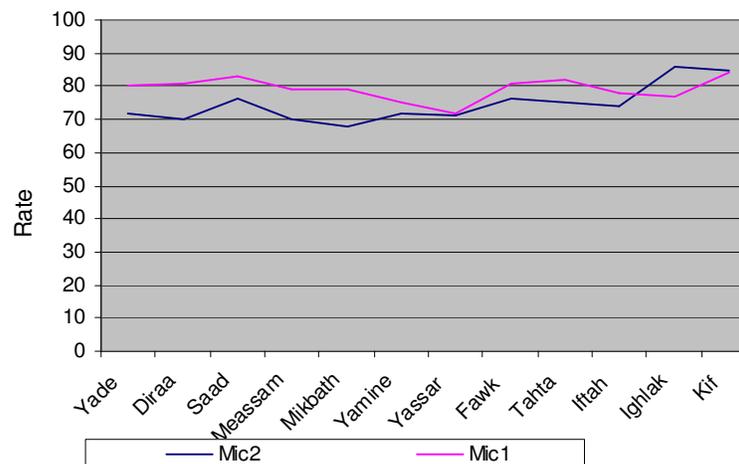


Figure 7c. Microphone effect on teh results.

within a hybrid design using a DSP and a microcontroller since it does not need too much memory capacity. Finally, since the designed electronic command for the robot arm consists of a microcontroller and other low-cost components namely wireless transmitters, the hardware design can easily be carried out as a future works (Kim et al., 1998; Fezari et al., 2005). Also, the application can be implemented on a DSP or a microcontroller in the future in order to be autonomous (Hongyu et al., 2004 [www.alzaytoonah.edu.jo/ICIT2009/documents/accepted %20papers.pdf](http://www.alzaytoonah.edu.jo/ICIT2009/documents/accepted%20papers.pdf)).

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