Embedded Speech Recognition System for Intelligent Robot

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**Abstract *—*** Automatic speech recognition (ASR) is a task that requires high computation capability and enough memory, which is difficult to work in the embedded devices. We have successfully developed an embedded speaker-independent speech recognition system. Specifically, we have also successfully designed a hardware module that can be embedded into the toy robot. We evaluated the speech-controlled robot and the recognition performance was quite good.

**Index Terms —**Automatic speech recognition, speech recognition

1. **INTRODUCTION**

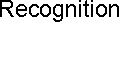
With the advances of information technology, the next generation of user interface is desired to be more friendly and powerful. As the most natural and expressive means of communication, speech is a suitable choice for the human- computer interaction. Furthermore, as we move from desktop PC to mobile phone, toy and other embedded devices, the user interface becomes smaller in size and the operation may thus be limited by facilities of hardware. Therefore, speech has the potential to provide a direct and flexible interaction for the embedded systems.

Speech control is dependent on the technology of automatic speech recognition (ASR) [1,2,3], the task of which can be speaker dependent or speaker independent. Generally, speaker-independent system is more widely used, since the user is not required to conduct the training. Speech recognition can be also divided into isolated word recognition, connected word recognition or large vocabulary continuous recognition. For the embedded device, it is generally enough to deploy isolated recognition system. And currently one typical application is for the toy which only requires simple and small-vocabulary command controls.

In this paper, we present our work of deploying a speaker-

disciplines, which include acoustics, phonetics, pattern recognition, statistics, probability theory, linguistics, and so on.

Speech recognition can be viewed as a pattern recognition task, which includes training and recognition. Generally, speech signal can be viewed as a time sequence and characterized by the powerful hidden Markov model (HMM) [1,2]. Through the feature extraction, the speech signal is transferred into feature vectors and act as observations. In the training procedure, these observations will feed to estimate the model parameters of HMM. These parameters include probability density function for the observations and their corresponding states, transition probability between the states, etc. After the parameter estimation, the trained models can be used for recognition task. The input observations will be recognized as the resulted words and the accuracy can be evaluated. The whole process is illustrated in Fig. 1.



**Fig. 1 Block diagram of automatic speech recognition (ASR) system**

*A. Hidden Markov Model*

HMM is a probabilistic pattern-matching approach which models a time sequence of speech pattern as the output of a stochastic or random process. HMM has been proven to be one of the most successful statistical modeling methods in the area of speech recognition [2,3].

The Markov generation model is a collection of states

independent speech recognition system for a popular intelligent robot. The organization of this paper is as

connected by transitions.

*aij*

 *P**q*

*t* 1 

*j* | *qt*

 *i* ,

follows. Section 2 has a brief introduction of automatic

 

**B** 

*b j* (**o***t* )

1  *i*, *j*  *N*

defines the probability of the transition

speech recognition. In Section 3, we address the designing issues of embedded speech recognition system. Section 4 describes the control mechanism of intelligent robot. Section

probability from state *qt* to *qt* 1 , in which *N* is the number of states. The output probability distribution can be

5 gives the evaluation results of the designed system.

represented as

, in which

Finally, we give the summarization of our work.

*b j* (**o***t*

)  *P***o***t*

| *qt*  *j*

1  *t*  *T* ,

*j*  1,2,⋯, *N*

1. **OVERVIEW OF SPEECH RECOGNITION** defines the probability of the observation which is equal to

The research of speech recognition originated as early as 1950’s [1]. This technology encompasses a wide range of

the symbol **o***t* in state *j*. The output probability distribution can be either discrete or continuous density. Currently it is

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very common to use the continuous density HMM, which has good ability to directly characterize continuous speech in the form of multi-dimensional real-valued feature vectors. The probability density function (pdf) of continuous HMM is usually in terms of Gaussian functions and has the

following form:

*C Tc*

 *c* ( *j*, *k* )**o***c*

*t*

*t*



***µ***  *c*1 *t* 1

*jk C Tc*

 *c* ( *j*, *k*)

*t*

*c*1 t 1

(5b)

*Tc*

*M*

*C*





  *c* ( *j*, *k*)(**o***c*  ***µ***

*bj* (**o***t* ) 

*c jk N* (**o***t* , ***µ*** *jk* , **Σ** *jk* ) 1 

*j*  *N* ,

*t*

*t*

)(**o***c*  ***µ*** )'

*k* 1

*jk*

*t*

*jk*

**Σ**  *c*1 *t* 1

(5c)

*jk C Tc*

1  *t*  *T*

*t*

(1)

 *c* ( *j*, *k* )

where *M* is the number of mixture per state, *c jk*

*t*

is the

*c*1 *t* 1

mixture coefficient for the *k*th mixture in state *j*, and *N* is

where

 *c* ( *j*, *k*) is the probability of being in state *j* at

the mixture Gaussian density function with the mean vector

***µ*** and covariance matrix **Σ** , which can be written as

*t*

time *t* with the *k*th mixture component accounting for **o** *c*

*jk*

*N* (**o** , ***µ*** , **Σ** ) 

*jk*

1 exp 1 **o**  ***µ***

(2 )*D* / 2 **Σ**

1/ 2

*jk*

' **Σ** 1 **o**  ***µ*** 

*t jk jk*

 2 *t*

*jk jk t jk* 

(2)

*C. Probability Calculation*

The task of isolated word recognition is to select the

where prime denotes vector transpose and *D* is the dimension of the vector **o** . The mixture gains *c* need to

word in the vocabulary with the maximum probability given the observation sequence **O** . Assuming that there are *V*

*t*

satisfy the following constraints,

*jk* words in the vocabulary, the maximum selection is defined

as

*cjk*

*M*

 1 , 1 

*j*  *N* , *c jk*  0

(3)

*v*

argmax*P*(*v*

*v*

| **O**,

1  *v*  *V*

(7)

*k* 1

The covariance matrix can be full or diagonal. It is common to use diagonal matrix for the mixture function,

where  represents the *v*th word model. According to the Bayes’ rule, we have

since linear combination of diagonal covariance Gaussians has the same model capability with full matrix and the

*P*(*v*

| **O**)  *P*(**O** | *v* )*P*(*v* )

*P*(**O**)

(8)

number of parameters of Gaussian mixtures densities can be

reduced. With the diagonal covariance matrix, the Gaussian pdf can be further expressed as:

 *o* 

*D* 2



1  1

*tl jkl*

Therefore, assuming that each word in the vocabulary has the same prior probability, the most possible word utterance only depends on the likelihood *P*(**O** | *v* ) .

*N* (**o***t* , ***µ*** *jk* , **Σ** *jk* ) 

*D* exp 2   2 

(2 ) *D* / 2 

*l* 1

*jkl*

 *l* 1

*jkl*



(4)

1. **EMBEDDED SPEECH RECOGNITION SYSTEM**

where *l* is the element index of the vector, *o* is the *l*th component of the feature vector **o***t* ,  *jkl* and  *jkl* is the *l*th mean and covariance in the *k*th mixture of the *j*th state,

*tl*

respectively. The denominator is dependent only on the

mixture of state. Therefore, we could precompute it and reserve the result for subsequent calculations during the training process.

*B. Model Train*

For continuous HMM, the re-estimation formulae for the observation density with multiple observation sequence are given as follows

*C Tc*

To deploy the embedded speech recognition system for small-size toy robot, two issues must be considered. First, a size-suitable hardware module should be designed that can be embedded into the body of robot. Second, the speech model and recognition procedure should be carefully selected or revised to work in the chip.

1. *Hardware Module*

Our embedded speech recognition system is based on a 16-bit chip, which is widely used in the areas of digital sound process and voice recognition. The memory capacity includes 4K-byte working SRAM plus a 64K-byte flash memory. And there are built-in microphone amplifier and

AGC function in this chip.

 *c* ( *j*, *k*)

*t*

*c*  *c*1 *t* 1

(5a)

To let the chip work, the module should be designed in which necessary peripheral circuits are added. Usually, this

*jk K*

*C Tc*

module is based on encapsulated chip and has a length of

 *c* ( *j*, *k*)

*t*

*k* 1 *c*1 *t* 1

105mm and width of 70mm. This size makes it difficult to be embedded into the body of toy robot.



**Fig. 2 The hardware module (TS\_ASR\_MODULE)**

Through special hardware technique based on naked chip, the size of our module (Fig. 2) was reduced to the length of 51mm and width of 32mm. This assured that it can be embedded into the body of toy robot. To communicate with the outside objects (e.g. motors in the robot), this module (TS\_ASR\_MODULE) provides 16 input/output (IO) ports (IOA0~7, IOB0~7).

1. *Speech Model*

The model unit of speech can be word, phoneme and triphone. While the sub-word unit such as phoneme or triphone has more flexibility for the extension of vocabulary [3], whole word was selected as the model unit for the embedded speech recognition system due to the chip’s limited memory capability. Since the recognition system is speaker-independent, the word model units should be trained based on the speech data collected from enough speakers. The range of speakers should cover different sex, age, region, and date.

The memory and processing capability of the chip was limited, and it doesn’t support the floating-point and other complex mathematical operations. Therefore, it is difficult to run the training procedure, which has high computation consumption and requires large memory for the training data to build speaker-independent system. To solve this problem, we detach the training procedure and recognition procedure. That is, the speech models are estimated off-line in the PC, and we use them to build the embedded recognition procedure in the chip.

the estimated models based on trained data can’t be used to make correct recognition of test data.

1. **SPEECH-CONTROLLED ROBOT**

The robot selected for our work is a popular toy, which can do six actions that are controlled by the electrical motors. Based on these six actions, we define the corresponding voice commands: Forward, Backward, Turn Left, Turn Right, Fire and Dance. And they are all uttered in Chinese.

During the recognition process, the response of speech- controlled robot is in real time. Once detecting the voice command, it would make the speech recognition and give a control signal to the corresponding IO port. As shown in Fig. 3, the motor connected with the port will then drive the robot to conduct the required action. For example, if we say the voice command of “Turn Left”, the ports of IOB6 and IOB7 will get a signal to drive the motor (Motor\_LeftLeg).

IOB6

Motor\_Head

Motor\_RightLeg

Motor\_LeftLeg

|  |  |
| --- | --- |
| T S  | A S R  | M O D U L E |  |
| IOB7 |
| IOA6 |
| IOA5 |
| IOA3 |
| IOA2 |
| IOA1 |
| IOA0 |
|  |

**Fig. 3 The IO ports of TS\_ASR\_MODULE to control the motors**

Motor\_Fire

Motor\_Push

1. **EVALUATION RESULTS**

*A. Training Database*

To build speaker-independent recognition system, the

*C. Recognition Procedure*

To build the chip-based speech recognition procedure, the original PC-based feature extraction and recognition procedure should be transformed line by line from float- point operation to fix-point operation. And the division and exponential operation also need to be replaced with digit- moving and log operation. Specifically, the training and recognition procedure must have the same feature extraction step. This is to assure the transformation from speech data to feature vector is uniform in these two procedures. Otherwise,

speech models of voice commands should be optimized based on the enough training database. In our experiment, the training database contains recordings of 40 male speakers and 40 female speakers. For each speaker, there are

6 commands recorded three times under the silent environment. Each recorded data consisted of up to 3s of utterance.

Before using for the training, the exact beginning and ending point of each utterance was adjusted carefully. This step was to discard the silence, noise and other part of the utterance. They were not true data from the recording speaker and might destroy the training performance. After

the training, the optimized models were downloaded into the embedded recognition system.

*B. Evaluation Results*

During the evaluation process, the speech-controlled robot would make real-time recognition and carry out the corresponding action. If the corresponding action matched the voice command, it meant that the recognition result was correct.

There were 80 testing speakers (not from those training speakers) selected in total and two evaluations were conducted: 68 speakers in normal environment and 12 speakers in noisy environment. The evaluation results were as follows.

**Table 1**

|  |  |  |  |
| --- | --- | --- | --- |
| Sex | Num | Age | Accuracy |
| Male | 49 | 20~29 | 100% |
| Female | 19 | 20~29 | 100% |
| Average |  | | 100% |

**Evaluation in normal environment**

As shown in Table 1, our embedded speech recognition system has perfect performance in normal environment. The recognition accuracy even reached 100%, which showed that our speaker-independent system was very robust for those testing speakers.

If the evaluated environment was very noisy, the speech recognition might be destroyed and the accuracy would be reduced distinctly. As shown in Table 2, the average accuracy of our evaluation was 91.7%.

**Table 2**

|  |  |  |  |
| --- | --- | --- | --- |
| Sex | Num | Age | Accuracy |
| Male | 3 | 10~49 | 88.9% |
| Female | 9 | 20~39 | 94.4% |
| Average |  | | 91.7% |

**Evaluation in noisy environment**

It can be demonstrated that noise was key factor that affect the recognition performance. So far, it is still one of the most difficult tasks in the area of automatic speech recognition. In the future, we’ll find more effective means to solve this problem.

1. **SUMMARY**

In this work, we have successfully developed an embedded speech recognition system that was speaker independent. The intelligent robot controlled by this system could well recognize the voice commands from the testing speakers and conduct the corresponding actions. 80 speakers

were selected to make the evaluation and the results were quite good. In normal environment, the recognition accuracy could reach 100%.

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