# Automatic Detection of Laughter using Respiratory Sensor Data with Smile Degree

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Abstract-Emotion detection in social activities is crucial for evaluating their effective interactions especially in group conversation. Among expressions of human emotions laugher is a part of human behavior regulated by the brain. It helps humans to clarify their intentions in social interaction and providing an emotional context to conversations. Automatic detection method of laughter is one of the leading indicators to verify whether participants are listening well or not with each other in group conversation. Thus, this study investigates the usability and simplification of laugher detection by developing a respiratory sensor using a dielectric elastomer, which is an elastic non-skin contact sensor, and combining its data with the smiling degree obtained by facial images. Experimental results of the integration of two sensor data, which are output data of HMM applied on the respiratory data and the smiling degree, suggest that it is possible to distinguish the states of laughing and not laughing during group conversation. This method can be applied for automatic detection of laughter.

*Keywords*—emotion detection, laughter detection, respiratory sensor, smile degree

#### I. INTRODUCTION

N recent years, a super aged society is facing problems of dementia of older adults. Dementia is one of the age related diseases with defect of memory. Lack of social interaction is thought to be one of the causes of dementia. In order to prevent dementia or mild cognitive impairment, social interaction is very important which activates social functions of the brain of participants. One form of social interaction is interactive group conversation. For making interactive group conversation for older people, Otake [1] has been proposing a Coimagination method, which helps the participants to participate equally into group conversation by sharing their experiences with the photos and time limit. This method activates multiple cognitive functions of the participants while recalling their memories, planning their talks, dividing attentions to both speeches and behaviors. In order to make interactive group conversation, we study and develop a system, which is capable of handling time limit of each speech, recognize some speech contents (certain words and laughter) and recognize facial expressions (emotions of the speaker) [2, 3]. If older adults participate effectively to group conversations by using their cognitive function, they will

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respond very interactively to speech of each other, such as nodding, laughing and so on at right time. In order to verify whether listeners interact well or not during group conversation, we need to detect laughter of each participant.

In literature, there have been many studies related to laughter detection based on different classification algorithms using many signal sources received from many kinds of sensors, such as acoustic signals, video signals, facial expressions and so on. Different types of features such as spectral and prosodic for laughter detection were investigated using different classification techniques including Gaussian Mixture Models, Support Vector Machines, Multi-Layer Perceptron which are often used in language and speaker recognition [4]. Knox and Mirghafori detects laughter automatically using Neural Networks based on extracted features, such as Mel-Frequency Cepstral Coefficients, pitch and energy, from acoustic signals [5]. Gaussian Mixture Models were trained with Perceptual Linear Prediction features, pitch and energy, pitch and voicing, and modulation spectrum features to model laughter and speech [6].

In real time laughter detection, we need sensors which is not complex, non-invasive and user friendly. We have developed a respiratory sensor with a dielectric elastomer which is applied on the abdomen of the subject.

In this study, we develop laugher detection system using the respiratory sensor which the participants are asked to wear on their abdomen, and smile degree calculated from facial image processing program, OKAO Vision, which is connected to conventional web camera.

For classifying states of laughing and not laughing, we applied Hidden Markov Model on the features extracted from the respiratory sensor data and then combined the results of HMM with the results of smile degree. Precision, recall, F-score and accuracy rate are calculated from the test results.

This paper is organized as followings. Section 2 describes experimental methods, including explanation of used sensors, experimental procedures and used methods for laughter detection. Section 3 shows the experimental results. Section 4 and 5 are for discussion and conclusion.

#### **II. EXPERIMENTAL METHODS**

- A. Used Sensors
- 1) Respiratory Sensor

The respiratory sensor was WOO3-1002-0002 of Wits. It was

developed jointly by Wits Inc. and Otake Laboratory, by using a dielectric elastomer for measuring the respiration. It is a non-skin contact and wearable sensor for an abdomen. Its dielectric elastomer is like capacitance-type pressure sensor adapted to be pressed against the human abdomen. The capacitance of the dielectric elastomer is changed by the protrusion of the disk-shaped sensing unit in the central portion of the respiratory sensor displaced according to the movement of the abdomen. The structure of the respiratory sensor system is shown in the upper part of Fig.1. Each respiratory sensor is attached to each participant's abdomen and the cables are connected to the multiplexer which is connected to the personal computer.

### 2) OKAO Vision System

Smile degree was calculated based on smile features from OKAO Vision, which is commercially available from OMRON, Inc. OKAO Vision software includes Smile Estimation Algorithm in the data processing unit. Smile degree is calculated from 0 degree to 100 degree based on the motion information of the mouth and eyes of tracked subjects face captured from a conventional web camera.. The system measures smile degree of the participants. It doesn't detect other emotions of faces, such as sad, angry, and so on.

## B. Experimental procedure

In the experiment, four subjects were participated, and their average age is 23. Namely, A, B, C, and D subjects, B, C are male and A, D are female. Every subject is asked to wear a respiratory sensor on their abdomen, and to look at a web camera located in front of them. Experimental setup is shown in Fig.1. Of each subject, the smile degree was calculated from OKAO Vision system with web camera, and the respiratory data was recorded in the computer using the respiratory sensor. In order to verify laugher detection using the developed sensor data, we did simple experiments. Experimental procedure is shown in below.

- 1. Take deep breathes for 30 seconds
- 2. Just breath as normal for 20 seconds
- 3. Speak one by one for 20 seconds
- 4. Watch a comedy movie (during this time, there is no any control for the body) for 3 minutes
- 5. Repeat steps 1 and 2.

During experiment, we also recorded a video of the experiments.

### C. Used Method for the laughter detection

From the recorded video, we judged real laugher states (laughing or not laughing) by our eyes. The recorded data from OKAO Vision system is used for distinguishing between laughter and a smile by setting a threshold value of 50%. If a smile degree is more than 50%, then the state is expected to be laughing, else the state is smiling. In this paper, we did not consider any degrees of laughter, such as little laughter or big laughter.

In Fig.2a, the recorded data from respiratory sensor with



Fig. 1 Experimental setup

description of experiment is shown. The calculated smile degree data is shown in Fig.2b. In order to classify the state whether laughing or not laughing, we quantized the data by five levels. For classifying the states of laughing or not laughing, we applied a Hidden Markov Model (HMM). HMM's parameters used in this paper is shown in Table I.

TABLE I Parameters of HMM					
The number of states of the model	N=2				
The number of distinct observation symbols per state	M=5, quantization data of the respiratory sensor				
The state transition probability distribution	$A = \{aij\}; a_{ij} = P(q_i = S_j   q_{i-1} = S_i)$				
The observation symbol probability distribution in state j	$b_j(k) = P(V_k \text{ at } t \mid q_t = S_j)$				
The initial state distribution	$\pi_i = P(q_1 = S_i)$				
The model parameters notation	$\lambda = (A, B, \pi)$				

From the experimental dataset, we extracted some dataset for a training dataset. We trained HMM from training dataset and extracted HMM parameters which are used for the testing dataset. Then, we also integrated the results of HMM with results of determined laughter from the smile degree.

### III. EXPERIMENTAL RESULTS

Results of HMM applied for the respiratory data are demonstrated in Fig.2c. From this result, we could see that the results of the respiratory data during deep breathing is sometimes recognized as laughing, because deep breathing signal includes features of laughing signal. In integration process, we just applied a simple a decision making method, which is that if laughter is detected in both results of smile degree and of HMM, classification state will be laughing, otherwise not laughing. Integration result is shown in Fig.2d. Fig.2e shows the real laughing state of the experiments. Comparing the results of HMM with real state of laughing, we



Fig. 2 Experimental Results

could examine that the laughing or not laughing states were classified well.

For evaluation of analysis of the HMM, we calculated precision rate, recall, F-score and accuracy rate. Table 2 shows the results of HMM for respiratory sensor data. In experimental results, recall is high and from 0.53 to 0.94, but precision is lower.

Accuracy rate of HMM applied respiratory data were from 79.32 to 94.31 percentage. Subject data with accuracy rate 79.32 was so noisy due to the subject's body motion. This means this respiratory sensor is good for less body motion. Finally, we combined the results of the HMM with the results of the smile degree, and calculated same values in previous case. Table 3 shows the combination results of HMM for respiratory data and smile degree. From Table 3, we could see that accuracy rate of integration of smile degree and HMM is improved than the result of only HMM. But precision, recall and F-score of it are reduced than the result of only HMM.

From accuracy of both results, integration of two sensory data helps to classify the states of laughing and not laughing at higher rate compared to only one respiratory sensor data. But F-score were less in both cases, because the number of the

TABLE II RESULTS OF RESPIRATORY SENSOR DATA

Respiratory sensor					
	Precision	Recall	F-score	Accuracy	
	rate			(100%)	
A	0.19	0.84	0.30	94.31	
В	0.06	0.53	0.12	86.41	
С	0.15	0.93	0.26	79.32	
D	0.04	0.83	0.07	88.08	

TABLE III
RESULTS OF RESPIRATORY SENSOR DATA + SMILE DEGREE

<b>Respiratory sensor + Smile degree</b>						
	Precision rate	Recall	F-score	Accuracy (100%)		
A	0.16	0.28	0.20	96.61		
В	0.07	0.01	0.02	98.08		
С	0.23	0.51	0.32	91.38		
D	0.04	0.43	0.08	94.19		

laughing states is very few in the experiments. In future, we have

to make experiments with many laughing states to improve system performance.

## IV. DISCUSSION

Change was observed in each output data of the respiratory sensor data, such as deep breathing, breathing, talking, and laughing. But output data of the respiratory sensor is corrupted by noise due to body movement of the subject. Deep breathing was sometimes detected as laughing state in the results of HMM, because the deep breathing state consists of resembling features to laughing. Seeing from the experimental results, precision, recall, F-score are small due to less number of laughing states. But accuracy rate is high and 80 to 98 percentage, which means that classification algorithm can classify two states of laughing and not laughing more than 80%. In order to get high precision, recall and F-score, we need to have more training data and to extract more features from the respiratory sensor data.

When we use only one sensor, a respiratory sensor for the detection of laughing or not laughing states, the results were not so good. In contrast when we use the data of the respiratory sensor with of smile detection sensor, the results were better than the results of only respiratory sensor for laughter detection.

We used a simple method for extracting features of HMM as a five level quantization. We can apply the same analysis protocol to different features such as Mel-Frequency Cepstral Coefficients, pitch, energy from the respiratory sensor data.

In this study, the number of classified states were limited to two; laughing and not laughing. In future, deep breathing will be added to the states to be classified.

#### V.CONCLUSION

This study demonstrates that laughter detection is implemented using the respiratory sensor which is developed by Otake laboratory and Wits Company, and the smile degree calculated from OKAO Vision software based on a conventional web camera. For classifying the states of laughing and not laughing, HMM is applied on the respiratory sensor data. Finally, we integrated the results of HMM with the smile degree data by applying a simple decision making process.

Experimental results proved that integration of two sensor data (respiratory sensor data and smile degree calculated from OKAO Vision) is better than only one respiratory sensor data for laughter detection.

In future, we will combine different source data such as acoustic signals, facial expressions and body motions with respiratory sensor data in order to detect laughter more precisely. Further experiments will be conducted with different age people in different environments.

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