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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