Feature Selection Guideline for Presence/Absence Classification Using a Microwave Doppler Sensor

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Abstract: Aging is a serious issue in our global society. In particular, a smaller working population increases the burden on nurses and other healthcare professionals. To reduce the monitoring burden on nursing, a system that enables quantitative monitoring of the elderly automatically in their home is very desirable. We have proposed a novel system to classify the presence or absence of a subject within a designated area using a single microwave Doppler sensor. The proposed system utilizes the respirational signal obtained from the sensor and then classified using an SVM. In this paper, we discuss feature components that would positively or negatively affect the performance of the system. The experimental results show that the combination of a demodulated time domain feature and frequency domain features affect positively to the accuracy of the system.

Key Words: microwave Doppler sensor, respiration, frequency domain, support vector machine, demodulation.

1. Introduction

Aging is a serious issue in our global society. The population of 60 years old and over is projected to be 1.4 billion by year 2030, and the number of people that require a high level of nursing care increases every year [1]. In addition, fewer people enter the healthcare workforce, which results in a larger burden on nursing and other healthcare staff. To reduce this burden, systems that enable quantitative monitoring of people in their homes are required. Thonmat proposed a system that uses long-time video to extract human activities [2]. Huang developed an activity recognition system using smartphones carried in pockets [3]. Methods proposed in [4]–[6] aim to monitor human activity using various sensors embedded in smart homes without requiring people to wear sensors. To enable such activity recognition systems, one fundamental feature is to classify the presence or absence of a subject within a designated area. Sekine and Okuya reported a human detection algorithm in [7]–[9]. [7] and [9] use a support vector machine (SVM) while [8] uses an autoregressive model. Under these circumstances, we have proposed a system that utilizes a feature vector with six components obtained from a microwave Doppler sensor to classify the presence or absence of a subject using a support vector machine (SVM) [10]. The six components of the feature vector could roughly be divided into two types: a) time domain features and b) frequency domain features. The system was evaluated using 21 subjects and can classify present-state or absent-state with 99.66% effectiveness in [10]. In this paper, we attempt to discuss feature components that would positively or negatively affect the performance of the system.

2. Proposed System

The proposed system consists of four steps: 1) observe microwave Doppler sensor signals and demodulate the signals; 2) calculate the feature vector; 3) select the combination of features; and 4) classify the presence or absence of a subject using the SVM. Figure 1 shows the block diagram of the proposed system.

2.1 Observation and Demodulation

The microwave Doppler sensor used in this paper has two components of signals as outputs: i) the in-phase signal $I(t)$ and ii) the quadratic signal $Q(t)$. Each signal is sampled into $I(k)$ and $Q(k)$, respectively.

Since $I(k)$ and $Q(k)$ are orthogonal, we calculate the demodulated signal $S(k)$ by

$$S(k) = \sqrt{I(k)^2 + Q(k)^2}.$$  

2.2 Feature Vector

As noted earlier, the observed signals and the demodulated signals are calculated into two types of features: a) time domain and b) frequency domain. Each type has three components. Because of the large difference in the observation value, we adopt logarithm features.

2.2.1 Three components of time domain feature vector

For the time domain feature vector, each signal $I(k)$, $Q(k)$, and $S(k)$ are squared and summed over $k$ denoted as $YI_T$, $YQ_T$, and $YS_T$ respectively:

$$YI_T = \log_{10} \left( \sum_k I(k)^2 \right).$$

$$YQ_T = \log_{10} \left( \sum_k Q(k)^2 \right).$$

$$YS_T = \log_{10} \left( \sum_k S(k)^2 \right).$$
Fig. 1 Overview of the proposed system. (1) Two observed signals from the microwave Doppler sensor are converted from analog to digital and demodulated to one signal. (2) These three signals are converted to the frequency domain. Then, the three components of the time domain feature vector and three components of the frequency domain feature vector are calculated. In total, six components of feature are obtained. (3) Next, we select the best combination of the features. (4) Finally, an SVM classifies the presence or absence of a subject.

2.2.2 Three components of frequency domain feature vector
To calculate the frequency domain feature vector, each of the signals is first converted into a frequency domain amplitude spectrum \( F_I(f) \), \( F_Q(f) \), and \( F_S(f) \), using the discrete Fourier transformation (DFT). The frequency domain features \( Y_{IF} \), \( Y_{QF} \), and \( Y_{SF} \) are the sum of the frequency domain power spectrum between \( f_{\text{start}} \) and \( f_{\text{end}} \):

\[
Y_{IF} = \log_{10} \left( \sum_{f_{\text{start}}}^{f_{\text{end}}} F_I(f) \right),
\]

\[
Y_{QF} = \log_{10} \left( \sum_{f_{\text{start}}}^{f_{\text{end}}} F_Q(f) \right),
\]

\[
Y_{SF} = \log_{10} \left( \sum_{f_{\text{start}}}^{f_{\text{end}}} F_S(f) \right).
\]

For this study, we are interested in the frequencies generated from human respiration. Therefore, we set \( f_{\text{start}} = 0.2 \) Hz and \( f_{\text{end}} = 0.8 \) Hz in the experiment presented below.

2.3 Feature Selection
In this paper, we attempt to observe and discuss the effect of selected features on the accuracy. Therefore, in order to find the best selected features, all possible combinations of the features from \( Y_{IF} \), \( Y_{QF} \), \( Y_{SF} \), \( Y_{IT} \), \( Y_{QT} \), and \( Y_{ST} \) are presented.

2.4 Classification Using SVM
Given the feature vector selected in Section 2.3, we classify the presence of the subject using the SVM. The output of the SVM \( \hat{Z} \in \{0, 1\} \) denotes the predicted presence of a subject within a designated area, where \( \hat{Z} = 1 \) represents the presence of a subject and \( \hat{Z} = 0 \) is the absence. We adopted a soft margin SVM and applied a radial basis function kernel.

3. Experiment
To find and evaluate the best combination of features, we tested our system by all combinations of features. Figure 2
shows an overview of our experimental system.

3.1 Materials

The microwave Doppler sensor used in this paper is IPS154 (InnoSenT). The in-phase and quadrature signals are amplified within the system board with gain +40 dB. An A/D converter AIO-160802AY-USB (Contec), 16 bit resolution (−10 V to +10 V), is connected to a Windows laptop via USB cable. A free logging software program provided by Contec, C-Logger, is used to collect $I(t)$ and $Q(t)$ with sampling frequency of 100 Hz. The duration of collection time was set to 30 s (3000 points).

In this experiment, the designated 2.0 m x 2.0 m square area is set as the experimental area in Fig. 3. The area is equally divided into $5 \times 5 = 25$ positions where each position is 0.5 m apart. Each position point is assigned a position number 1 to 25. The sensor device is mounted 2.3 m above the floor, just above the center of this experimental area (position number 13). This height was selected because the height of the ceiling in most residences is about 2.3 m from the floor.

In this experiment, 25 subjects participated who participated with our informed consent. The subjects were 20 males and 5 females and ranged in age from 20 to 35 years old. Note that we added four more subjects from the experiment described in [10].

3.2 Methods

The subjects were seated at each position (1-25) in the experimental area. In each experimental area, the sensor data obtained during about 30 seconds. The distance from the sensor device fixed at position 13 critically affects the values of the feature vector used in this system. In total, we obtained 25 data points for each subject. The total number of “present” data is 625.

The same number of “absent” data was also collected where no humans are present in the same experimental area. The total number of absent data is 625. Therefore, the sensor device is fixed at position 13 for both presence and absence data measurements.

3.3 Evaluation

The performance of the proposed system is evaluated by a leave-one-subject-out manner and its accuracy, precision, and recall values are reported. Given a test dataset where true presence/absence is known, the predicted result is classified into four groups in the Prediction Matrix shown in Table 1. A true positive count (TP) is the number of data where the system estimated presence and the true data indicated presence. A true negative count (TN) is the number of data where the system estimated absence and the true data indicated absence. A false positive count (FP) is the number of data where the system estimated existence but the true data indicated absence (also known as Type I error). A false negative count (FN) is the number of data where the system estimated absence, but the data indicated presence (also known as Type II error).

Using the numbers in the Prediction Matrix, the accuracy, the precision, and the recall are defined as follows:

\[
\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN},
\]

\[
\text{Precision} = \frac{TP}{TP + FP},
\]

\[
\text{Recall} = \frac{TP}{TP + FN}.
\]

The accuracy, precision and recall are obtained for each combination. As the best combination, the combination that can be evaluated with the highest accuracy is selected.

In order to evaluate the validity of applying SVM, we compare the accuracy, the precision and the recall between SVM and Naive Bayes classifier.

4. Experimental Result

4.1 Observed Data

4.1.1 Typical observation of the presence data

Figure 4(a) shows typical observed data where a subject (ID1) is located at position number 13. The top three plots show the time series plots of the signals $I(k)$, $Q(k)$, and $S(k)$, whereas the bottom three plots show the amplitude spectrum of each of the signals $I(k)$, $Q(k)$, and $S(k)$. Figure 4(b) shows typical observed data where the same subject (ID1) is located at position number 25. Notice that when a subject is present near the sensor device, such as position number 13, time-series and frequency data vary substantially, but when a subject is located far from the sensor device, such as position number 25, the amplitude in the time series plot is low and the power spectrum is flat.

4.1.2 Typical observation of the absence data

Figure 4(c) shows the typical observed data where a subject is absent from the experimental area. Notice that the amplitude is low in the time domain plot and the amplitude spectrum is flat in frequency domain plots.

4.2 Calculated Feature Vector

Figure 5 shows a scatter chart of all the combinations of the calculated six-dimension features $Y_{F_k}$, $Y_{Q_k}$, $Y_{S_k}$, $Y_{I_k}$, $Y_{Q_k}$, and $Y_{S_k}$. The dots represent the presence data, and the crosses represent the absence data. Notice that both time domain fea-

![Fig. 3 Partitioning of the experimental area. The number in the circle denotes the position number. The microwave Doppler sensor is set 2.3 m above from position 13.](image-url)
Fig. 4 Typical observation data. From the top row, plots of observed signals $I(k)$ and $Q(k)$ from the microwave Doppler sensor IPS-154, the demodulated signal $S(k)$, and their frequency domain amplitude spectrum $F_1(f)$, $F_Q(f)$, and $F_S(f)$. (a) is typical observation data at position number 13, the center of the experimental area. (ID1) (b) is typical observation data at position number 25, one of edges in the experimental area. (ID1) (c) is typical observation absent data where a subject is absent and nobody is in the experimental area.

4.3 Classification Results

The precision of all calculations is 100%, thus we evaluate
the best combination in terms of accuracy. The result is shown in Table 2. The highest degree of accuracy is 99.76% when three types of combination are used. The highest degree of accuracy is 99.76% when all six components are used (result 1). Although the experimental setting is the same as those reported in [10], because we added four more subjects, we obtained slightly different accuracy. Eliminating some compo-
Table 2 Accuracy of all combinations (%).

| result No. | combination of features | the accuracy (rank) |
|------------|-------------------------|---------------------|
| 1          | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{T}$ | 100% (1)            |
| 2          | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{Q}$ | 99.99% (2)          |
| 3          | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_S$ | 99.98% (3)          |
| 4          | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{QT}$ | 99.97% (4)          |
| 5          | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{QF}$ | 99.96% (5)          |
| 6          | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.95% (6)          |
| 7          | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.94% (7)          |
| 8          | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.93% (8)          |
| 9          | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.92% (9)          |
| 10         | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.91% (10)         |
| 11         | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.90% (11)         |
| 12         | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.89% (12)         |
| 13         | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.88% (13)         |
| 14         | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.87% (14)         |
| 15         | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.86% (15)         |
| 16         | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.85% (16)         |
| 17         | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.84% (17)         |
| 18         | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.83% (18)         |
| 19         | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.82% (19)         |
| 20         | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.81% (20)         |
| 21         | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.80% (21)         |
| 22         | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.79% (22)         |
| 23         | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.78% (23)         |
| 24         | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.77% (24)         |
| 25         | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.76% (25)         |
| 26         | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.75% (26)         |
| 27         | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.74% (27)         |
| 28         | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.73% (28)         |
| 29         | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.72% (29)         |
| 30         | $Y_t^1$, $Y_q^1$, $Y_s^1$, $Y_{ST}$ | 99.71% (30)         |
| 31         | $Y_t^1$, $Y_q^1`, $Y_s^1`, $Y_{ST}$ | 99.70% (31)         |
| 32         | $Y_t^1`, $Y_q^1`, $Y_s^1`, $Y_{ST}$ | 99.69% (32)         |

Table 3 Average result of classification (%).

| | Naïve Bayes | SVM |
|---|-------------|-----|
| Accuracy | 98.00±2.38 | 99.76±0.66 |
| Precision | 100.00±0.00 | 100.00±0.00 |
| Recall | 96.34±4.27 | 99.54±1.28 |

Table 4 Accuracy of each seating position. (%) The number in the bracket denotes the position number. The positions where accuracy was 100% are shown in gray background.

| (1) | 96.00 |
| (2) | 100.00 |
| (3) | 100.00 |
| (4) | 100.00 |
| (5) | 100.00 |
| (6) | 100.00 |
| (7) | 100.00 |
| (8) | 100.00 |
| (9) | 100.00 |
| (10) | 100.00 |
| (11) | 100.00 |
| (12) | 100.00 |
| (13) | 100.00 |
| (14) | 100.00 |
| (15) | 100.00 |
| (16) | 100.00 |
| (17) | 100.00 |
| (18) | 100.00 |
| (19) | 100.00 |
| (20) | 100.00 |
| (21) | 100.00 |
| (22) | 100.00 |
| (23) | 100.00 |
| (24) | 100.00 |
| (25) | 100.00 |

5. Discussion

The experimental results show that using all the six components would show the best performance (result 1). Eliminating the two time domain features $Y_{T}$ and $Y_{QT}$ did not affect the performance (result 22). On the other hand, if we only use $Y_{T}$ and $Y_{QT}$, the accuracy was the lowest among the results (result 43). This implies that $Y_{T}$ and $Y_{QT}$ are not suitable for absence or presence classification. If we use only the frequency domain features (result 42), the accuracy slightly decreases. This implies that the combination of the demodulated time domain feature and the frequency domain features affect the accuracy of the system positively. With only one feature, they still provide relatively high accuracy. Within the experimental results of only one feature, the frequency domain features provide better accuracy than the time domain features. Feature $Y_{QF}$ gave the highest accuracy (result 62), followed by $Y_{IY}$, $YSF$, $YSF$, $YSF$, and $Y_{QT}$. With $Y_{QF}$ and $Y_{IY}$, the accuracy is 99.28% (result 55), slightly higher than result 62. This implies that by adding the feature $YSF$, the hyperplane could classify the feature vector into presence and absence, whereas only one feature $Y_{QF}$ could not. The main reason is that the features capture periodic human motions, such as respiration and heartbeat. The microwave Doppler sensor can observe such periodic movements. The frequency domain features are designed to take in such respirational movements. On the other hand, the time domain features are designed to incorporate non-periodic movements. Taking into account too many non-periodic movements

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tends to degrade the performance.

Although precise comparison is difficult since the experimental settings is different, [9] reports the presence-absence classification accuracy of methods proposed in [9] and [7] as 91.4% and 89.4%, respectively. The proposed method performed better than the methods used in [9] or [7]. One reason that the proposed system shows high accuracy is that the frequency domain features account for only the frequencies generated from respiration of the subject.

The precision reported in [9] and [7] were 86.2% and 86.4%, respectively, where our method has an accuracy of 100%. The recall reported in [9] and [7] were 93.4% and 90.5%, respectively, whereas that of our method was 99.54%. This shows that the system did occasionally predict that the subject was absent even if the subject was present in the experimental area. This would be only a minor problem in actual use because a caregiver can confirm the true state of presence or absence in these rare instances.

Although precise comparison is difficult, one reason our method performed better is because the device in literature [7] was set on the desk, where our method was set on the ceiling. As shown in Fig. 3, the microwave Doppler sensor can detect objects within a conical space. Setting the device on the desk would make the subject easily move outside this conical space. Compared with [10], two features are reduced with same degree of accuracy, thus the proposed method is more useful.

6. Conclusion

We have proposed a novel system to classify the presence or absence of a subject within a designated area using a single microwave Doppler sensor. The proposed system utilizes the respiration signal obtained from the sensor and then classified using an SVM. In this paper, we discussed which type of feature components would positively or negatively affect the performance of the system. The system was evaluated using 25 subjects and was able to classify the presence of a human subject within an area of $2.0 \text{m} \times 2.0 \text{m}$ with the accuracy of 99.76%. The experimental result shows that the combination of the demodulated time domain feature and the frequency domain features affect positively to the accuracy of the system.

Although the proposed system produces reasonable results, as future work we will follow up with following experiments. We expect to cover a larger area by incorporating multiple sensor devices simultaneously. In addition, the state of presence has to be divided between “rest-state” and “move-state.” With these classifications, we can recognize any activities such as wandering. In addition, the experimental field reported in this paper was an ideal laboratory setting field. The performance of our method in actual environment is interesting.

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