SCIENCE CHINA
Information Sciences

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August 2018, Vol. 61 084301:1–084301:3
https://doi.org/10.1007/s11432-018-9395-5

Bowel sound recognition using SVM classification in a wearable health monitoring system

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Received 18 January 2018/Accepted 21 March 2018/Published online 4 June 2018

Citation Yin Y, Jiang H J, Feng S L, et al. Bowel sound recognition using SVM classification in a wearable health monitoring system. Sci China Inf Sci, 2018, 61(8): 084301, https://doi.org/10.1007/s11432-018-9395-5

Intestinal motility (IM) assessment, which is used in many clinical applications, monitors bowel sounds (BSs) to diagnose digestive tract activity in real time and validate post-operative ileus [1–4]. For patients with IM problems, effective BS monitoring is helpful for health evaluation and early-nursing assessments, resulting in reduced in-hospital time, resource utilization and operational costs [2, 3]. However, IM monitoring and recognition procedures typically rely on subjective and time-consuming auscultation by stethoscope, which can delay diagnosis [3]. Automatic BS event recognition and IM evaluation would enable more effective healthcare in clinical applications, in which the key step in BS processing is the precise appearance recognition and location of each BS event.

The prototype BS monitoring system. In this study, we constructed a wearable prototype bowel sound monitoring system comprising a miniature wearable bowel sound recorder, a wireless data gateway, and a computer for signal processing. In this system, the gateway receives sound data wirelessly from the recorder through a Bluetooth link, and sends the data to the computer via an Ethernet cable. The battery operated BS recorder is attached to the lower right abdomen, while the subject is lying supine, by a surgical dressing far away from the chest to avoid the cardiac sound interference. The audio processor in the gateway provides .wav files to the computer. Figure 1(a) shows the prototype system architecture. We validated the recognition algorithm used in this system, which is explained below.

BS recognition and intestinal motility evaluation. Legendre polynomials have been verified as feasible for fitting biometric signals and preventing interference from sharp frequency peaks or other jitter noises with reduced storage space [5, 6]. In our previous study [7], we used Legendre-fitted BS spectrum model for correlation detection, yet this approach dropped much of the spectral information and can fail because it labels only BS events $>$ 3 s without any clear starting/ending points. We propose an improved method for BS event recognition and IM evaluation based on Legendre-fitting spectra.

In the algorithm, each m-second sample segment $\boldsymbol{y}$ with the sample rate $\mathrm{Fs} = 4$ kHz is divided into one-second intervals $\boldsymbol{y}_i\{s\}$, and the normalized logarithmic magnitude spectra $\boldsymbol{S}_i$ of $\boldsymbol{y}_i$ are obtained by fast Fourier transform as follows:

$$\boldsymbol{S} = [\boldsymbol{S}_1, \boldsymbol{S}_2, \boldsymbol{S}_3, \ldots, \boldsymbol{S}_m]_{\frac{\mathrm{Fs}}{2}\times m}. \tag{1}$$

The smoothed spectrum sequence $\boldsymbol{S}^*$ free of sharp jitters is reconstructed as follows:

$$\boldsymbol{S}^* = [\boldsymbol{S}_1^*, \boldsymbol{S}_2^*, \boldsymbol{S}_3^*, \ldots, \boldsymbol{S}_m^*]_{\frac{\mathrm{Fs}}{2}\times m}. \tag{2}$$

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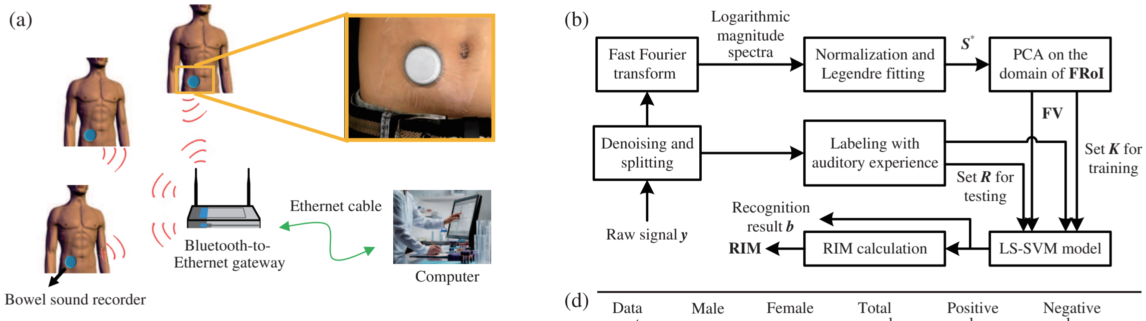

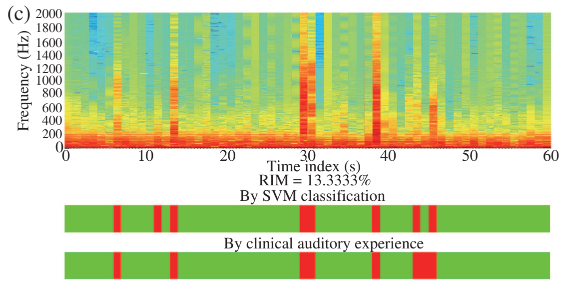

(d)

Data set	Male	Female	Total sample	Positive class	Negative class
K	9	5	9420	3454	5966
R	4	2	6300	1399	4901

(e)

	BS data amount	Number of subjects	Acc (%)	Sen (%)	Spe (%)
[2]	3213 s	10	94.15	35.23 in total	95.05 in total
[10]	301 BS events	10	up to 82.72	up to 89.56	–
This study	4853 s	20	90.10	86.80	91.10

Figure 1 (Color online) The prototype of BS monitoring system. (a) System architecture; (b) BS processing flow; (c) system output; (d) composition of samples in different data sets; (e) comparison results with previous literatures.

The observable frequency band of $f \in [0, \mathrm{Fs}/2]$ is linearly normalized to $x \in [-1, 1]$ as follows:

$$f = \left(\frac{\mathrm{Fs}}{2} - 0\right) \cdot \frac{x - (-1)}{1 - (-1)}. \tag{3}$$

The j-th point $S^*_{i,j}$ $(1 \leqslant j \leqslant \mathrm{Fs}/2)$ of $\boldsymbol{S}^*_i$ within the M-dimension Legendre subspace is determined by the following:

$$S^*_{i,j}(x) = \sum_{r=0}^{M} f_{i,r,j} P_r(x), \tag{4}$$

$$f_{i,r,j} = \frac{\int_{-1}^{1} S_{i,j}(x) P_r(x) \mathrm{d}x}{\int_{-1}^{1} P_r^2(x) \mathrm{d}x}, \tag{5}$$

$$r = 0, 1, 2, \ldots, M,$$

$$P_r(x) = \frac{1}{2^r r!} \frac{\mathrm{d}^r}{\mathrm{d}x^r}[(x^2 - 1)^r]. \tag{6}$$

An n-Hz frequency range of interest (FRoI) is selected that corresponds to where bowel signal spectrum is mainly distributed, which reduces $\boldsymbol{S}^*$ to n rows, and is then decorrelated to a t-row matrix $(t \ll n)$ **FV** with m feature vectors by principal component analysis as follows:

$$\mathbf{FV} = [\mathbf{fv}_1, \mathbf{fv}_2, \mathbf{fv}_3, \ldots, \mathbf{fv}_m]_{t \times m}. \tag{7}$$

The one-second sound pieces are labeled as either 1 or 0 depending on the occurance of BS, based on the gold standard of clinical auditory experience. In this study, we randomly divided the subjects whose BSs were to be recorded into two groups, and labeled the data as training set $\boldsymbol{K}$ and test set $\boldsymbol{R}$, respectively.

We constructed an SVM using the least square method with the radia-basis function kernel for trade-offs between complexity, range and convergence. The kernel width σ must be optimized to avoid numerical calculation problems. We used 10-fold cross-validation as the cost function. $\boldsymbol{R}$ simulates the trained SVM for the output classification label $b_i\{s\}$ with a one-second resolution for the appearance of BS events. We calculated corresponding accuracy (Acc), sensitivity (Sen) and specificity (Spe) after comparing the true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN) as follows:

$$\mathrm{Acc} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}, \tag{8}$$

$$\mathrm{Sen} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}, \tag{9}$$

$$\mathrm{Spe} = \frac{\mathrm{TN}}{\mathrm{FP} + \mathrm{TN}}. \tag{10}$$

The relative intestinal motility (RIM) in a T-second time period is defined as follows [7]:

$$\mathrm{RIM} = \frac{1}{T} \sum_i b_i \times 100\%. \tag{11}$$

Figure 1(b) illustrates the flow chart of the BS classification procedure.

Experiment setup and results discussion. In the experiment we recorded BSs in quiet rooms in which there was no talking, no persons who were not involved in the experiment, and with all clinical equipment switched off. We collected the BSs of 20 volunteers including 7 females and 13 males. To attenuate various noise disturbances, we applied the spectral subtraction method to the signal records, which we split into 1-minute segments. We carefully extracted at least 11 segments with valid BS signals from each subject. Then, we divided each segment into 60 one-second pieces which were then labeled by experienced doctors. Figure 1(d) lists the numbers of volunteers and sample pieces in $\boldsymbol{K}$ and $\boldsymbol{R}$. Considering the BS spectrum and previous literatures [7–9], we set the FRoI to (100, 1400] Hz and determined the M and t values to be 15 and 10 respectively as a best compromise between calculation complexity and precision.

We determined the number of TP, TN, FP and FN to be 1214, 4467, 434 and 185 respectively, with $\sigma = 0.726$ giving the best SVM performances. The FNs may be attributed to subjective judgement in which weak signals are omitted, whereas FPs may occur in various noise environments that share the BS spectrum. Compared to previous studies [2, 10], this system provides better-balanced sensitivity and specificity as shown in Figure 1(e). In addition, in contrast to our previous study [7], this system can also explicitly report the starting/ending points and duration of each BS event with a one-second resolusion. The above-described algorithm is used as a MATLAB function displaying a color bar as the system output by labeling the appearance of BS events in red with the corresponding RIM based on the input $\boldsymbol{y}$ in $T = 60$ s. Figure 1(c) shows a typical test result. As such, these results validate the proposed algorithm, which can be used for non-invasive clinical IM monitoring.

Conclusions and future work. We constructed a wearable bowel sound monitoring system using off-the-shelf components. We proposed a new algorithm for quantitative BSs classification and RIM assessment, and validated its effectiveness on the system. The feature vectors for LS-SVM classification are composed of principal components of Legendre-smoothed signal spectra, and we proposed a subsequent RIM measurement procedure based on the SVM output. The BS event recognition results indicate that the proposed method provides greater than 90% accuracy and specificity, and greater than 85% sensitivity. The duration of BS events with their corresponding RIM are graphically output for clinical IM assessment.

Future research will focus on overcoming the failure that occurs when BSs are collected in the presence of speech and machinery sounds by updating the SVM with a more effective kernel. We will also indentify a BS-diagnosis approach specific to certain intestinal diseases and establish a large unifying database covering multiple ages, body mass indices. This system will also be extended for application to other bodily sounds in wearable health-care monitoring.

Acknowledgements This work was supported in part by National Natural Science Foundation of China (Grant Nos. 61474070, 61431166002, 61661166010), and Beijing Engineering Research Center (Grant No. BG0149). The authors would like to thank the doctors who contributed to the experiments, including Ms. Huili KAN from Department of Anesthesiology, Liaocheng People's Hospital and Mr. Jianjun LI from Department of Gastrointestinal Surgery, Liaocheng People's Hospital.

Supporting information The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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