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Combining Neural Network and Wavelet Transform for Trigger Asynchrony Detection

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Abstract—Trigger asynchrony is a phenomenon when the ventilator is out of synchronization with breathes of respiratory patients. The occurrence of trigger asynchrony would cause discomfort and harms to the patients. Thus understanding the trigger asynchrony situation for better setting the ventilator parameters to lower the possibility of occurrence of trigger asynchrony is critical to respiratory patient care. This paper proposes the combination of neural networks and wavelet feature extraction for trigger asynchrony detection. The performances using various training situations are also compared. A breath cycle is composed of inspiratory phase and expiratory phase. In this paper we also explore the performance differences between the situation when the neural network detection is applied with the same trained neural network for inspiratory and expiratory phases and the situation when the detection and is applied with different neural network for inspiratory and expiratory phases. It was found that although separating detection with different neural networks for the inspiratory and expiratory phases requires slightly more time, it achieves higher performance than that the detection is applied with the same neural network for both phases. The results are also compared with the results by physicians' observations for accuracy evaluation.

I. INTRODUCTION

Respiratory failure is a life-threatening condition in which the body's respiratory apparatus is unable to provide adequate delivery of oxygen to the blood and removal of carbon dioxide from the blood. Mechanical ventilation can effectively assist breathing in respiratory failure by taking over the vital role of the respiratory muscles, inducing rhythmic inflation and emptying the lungs, decreasing the work of breathing, supporting the gas exchange, etc.

In some mechanical ventilation modes, the ventilator pressure support is triggered by the inspiratory effort of the patient. There are many causes which may result in trigger asynchrony (TA)[1][2]. Trigger asynchrony may cause the patient uncomfortable and harms to the patients. As such, detection of trigger asynchrony is considered one important issue for providing high quality health care to respiratory patients.

Currently Trigger asynchrony detection relies on observance of the patient, the airway pressure or airway flow waveform by doctors, respiratory therapists and nurses, which not only requires high human attention and is also not timely. Based on these considerations, this paper explores the detection of trigger asynchrony by combining the neural networks and wavelet features. A breath cycle is composed of inspiratory and expiratory phases. Basically the inspiratory and expiratory phases TAs expose slight different features. Thus it is expected that separating the detection into inspiratory TA detection and expiratory TA detection could increase the performance. However this separation also implies more training effort and slightly more detection time. In order to understand the difference between these two situations, this paper also explores the performances of TA detection in the two situations.

Based on the aforementioned descriptions, the process of this paper contains the inspiratory and expiratory phases segmentation. A soft-thresholding de-noising algorithm[9] is applied to remove the turbulence noises. Then, in the 2nd phase, "wavelet transformation with thresholds" which will be described in detail later is applied on the inspiratory phase signal and expiratory phase signal separately for trigger asynchrony candidate selection. The classification phase uses multilayer perceptrons neural network (MLPNN)[11] to recognize TAs in TA candidates. The recognition accuracy of the algorithm will be compared with the recognition accuracy of the human eye. The architecture of the algorithm is illustrated in Fig. 2.

The remaining parts of the paper are organized as follows. Section II describes the segmentation of the breath cycle into inspiratory and expiratory phases. The soft threshold de-noising method is also described in this section. Section III addresses the selection of TA candidate based on the wavelet subband data. The trigger asynchrony detection with multilayer perceptrons neural network was illustrated in

Section IV. The experimental results were illustrated in Section V. Finally Section VI draws the conclusions.

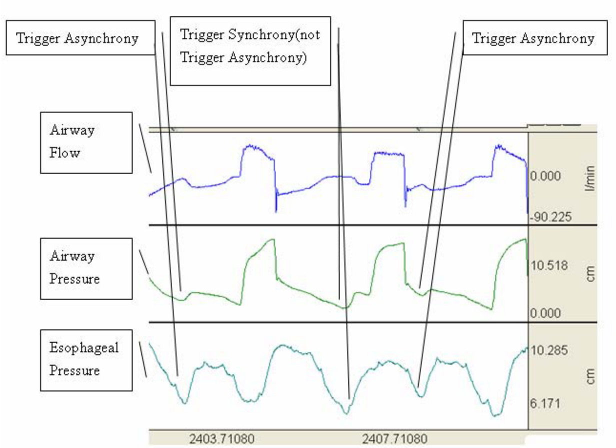

Fig. 1 The waveform of trigger asynchrony and waveform similar with but not trigger asynchrony.

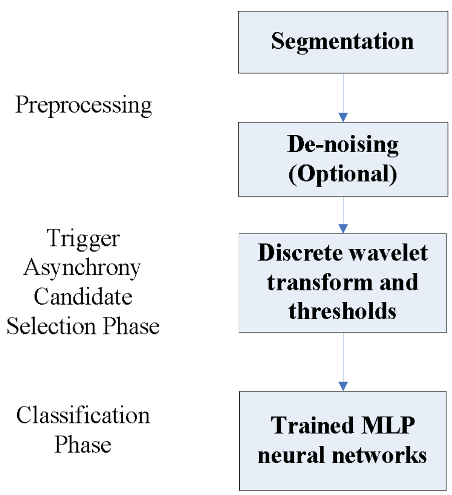

Fig. 2 Architecture of the algorithm.

II. INSPIRATORY AND EXPIRATORY PHASES SEGMENTATION

The respiratory waveform can be partitioned into inspiratory phase and expiratory phase. The phenomenon of trigger asynchrony is slightly different in the inspiratory phase and the expiratory phase. Furthermore, the transition period near the boundary of the inspiratory phase and the expiratory phase exposes some signal feature similar to trigger asynchrony, for example, the trigger synchrony shown in Fig. 2. Thus it is expected that separating the detection into inspiratory TA detection and expiratory TA detection would increase performance. As such, in this section the breath cycle is segmented into inspiratory phase and expiratory phase. A period of inspiratory phase or expiratory phase is called a segment for simplicity.

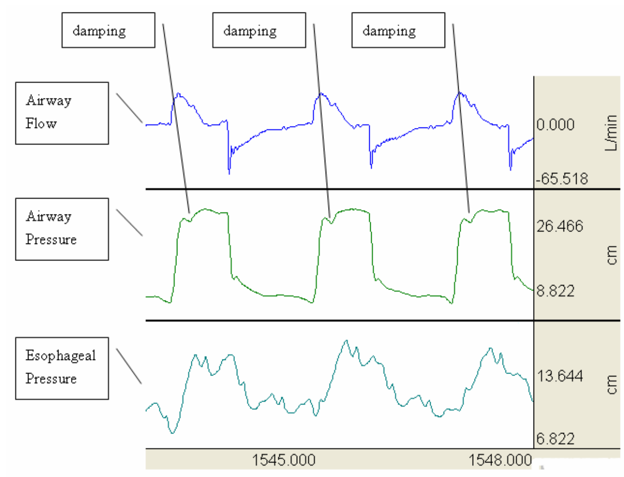

Fig. 3 the damping like inspiratory TA and inspiratory TA

In most case, the airway flow is positive in the inspiratory phase and negative in the expiratory phase. When the phase changes from inspiratory phase to expiratory phase, the airway flow crosses zero point. Thus this paper adopts "zero airway flow rule" for the phase segmentation: A point at time t (second) is defined as a zero cross point if $S(t)*s(t-0.01)<0$ or $[s(t)=0$ and $s(t+0.01)\neq 0]$. However, usually there are small local flows causing the airway flow damping around the zero crossing point. Thus the breath time frequency in physical situation is taken into consideration for avoiding the interferences from damping phenomenon. Consider the general situation that breath frequency would not be higher than 50 times per minute. Also the inspiratory phase and the expiratory phase would not be shorter than 1/4 of a breath cycle. Thus if we let C_j, $1\leq j\leq m$, where m is the total number of zero-cross point, be the zero-cross points, the zero cross point C_k would not be considered a segmentation point if the time period between C_k and C_{k+1} is smaller than 1/4 of breath cycle, which is 60/(50*4).

Once a breath cycle is segmented into inspiratory phase and expiratory phase, the results are applied to a soft-threshold based de-noising process.(This step is optional) The de-noising process employs a derived soft threshold on the frequency domain signals which has been processed by a low pass filter and boundary effect canceller to remove the noises which is assumed to be Gaussian distribution.

III. TRIGGER ASYNCHRONY SELECTION

The trigger asynchrony is considered the 1 cmHg esophageal pressure (P_{es}) drop[3] as shown in Fig. 1, where we can also usually see that the drop of esophageal pressure leads to the drop of airway pressure (P_{aw}) and the rise of airway flow. In clinic, the normal characteristic of trigger asynchrony is found to have a u-shaped(or v shaped for some shapes are like v character) local minimum with 0.3~2 sec width. However several other situations may also cause the U(or v) shaped(or v shaped) signal[8]. Consequently, how to detect the local minimum u(or v) shaped signal without interfered by the noises is the key essential in the detection of trigger asynchrony. The algorithm will be introduced in this section is called "wavelet transformation with thresholds".

Wavelet transform has the capability of extracting local frequency characteristic [4][5]. Thus it is employed to extract the local u(or v) shaped feature for trigger asynchrony detection. Discrete Wavelet Transform(DWT) has several characteristics such as multiresolution and subband concepts. The DWT generate a set of expansion functions such that any signal in $L^2(R)$ (the space of square integrable functions) can be represented by the series:

$$f(t)=\sum_{j,k} a_{j,k} 2^{j/2}\psi(2^j t-k) \quad (1)$$

where the two-dimensional set of coefficients $a_{j,k}$ is called the discrete wavelet transform (DWT) coefficients. [5] The wavelet transform decomposes the signal into different levels which differ in the series of low-pass or high-pass filters applied [6].

After wavelet decomposition, the TA's local frequency should be evaluated for selecting the subbands for analysis. Based on the physical phenomenons, the width of an TA is 0.3~2sec, which implies that the cycle of the main frequency component of a TA is generally 0.6~4sec. Thus, the frequency of TA is generally in the range of 0.25~1.67Hz. From practical situations it is also found that the width of TA is mostly in the range of 0.3~0.7 sec. So the main frequency component of TA is in the range of 0.714~1.67 Hz which covers the frequency bands of d_6 and overlaps with the frequency bands of d_5 and d_7 [7] as listed in TABLE I. Within the three frequency bands, d_5 has the highest resolution, d_6 reveals as the most dominant frequency band. Comparatively, d_7 has less resolution and only occasionally occurs. Thus in our approach d_5 and d_6 are adopted as the major frequency bands for TA analysis and detection.

TABLE I
THE FREQUENCY BANDS OF D_5,D_6 AND D_7 WITH 0.01 SECOND SAMPLING TIME.

Decomposition	Band range(Hz)
d_5	1.5625~3.125
d_6	0.78125~1.5625
d_7	0.390625~0.78125

For TA detection from the frequency bands, firstly the local minimum points are found by the following criteria: $d_l[x+1]-d_l[x]>\theta_L$ and $d_l[x-1]-d_l[x]>\theta_L$, where $d_l[x]$ means the value of xth point of l level wavelet decomposition and θ_L is the threshold for the local minimum, named local minimum depth threshold(LMDT). These detected local minimum are chosen as possible TA. However, there are several situations which may cause the false TA. As such they need to be considered to remove the false TA, as described in the following. (A) In the inspiratory phase, there are damping signals which also expose the local minimum feature as shown in **Error! Reference source not found.**. The candidates exposing damping are filtered by the following criteria: if $d_l[x-1]-d_l[x-2]>th_s$, this candidate is a damping. (B) When a breath triggers the ventilator to support the patient's breath successfully, the u(or v) shape of airway pressure which is trigger synchrony as shown in Fig. 1 also causes the local minimum and may be misrecognized as TA. Since the successful trigger is often followed by a climbing-up shape of P_{aw} and it is often at the beginning of inspiratory phase, thus a detection of steep (climbing-up) or flat is performed: If $d_l[x]-d_l[x-1]<th_f$, the edge is flat. On the other hand if $d_l[x]-d_l[x-1]>th_s$, the edge is steep. If it is flat, the number of flat occurring is then counted. If the occurrence is greater than tth_f(flat time threshold), the u(or v) shaped local-minimum is considered a TA. On the other hand, if it is a steep edge, the number of steep edge occurrence is also counted. If the number is greater than tth_s(steep time threshold), the u(or v) shaped local-minimum is not TA candidate. For the remaining if flat count is smaller than tth_f and steep count is smaller than a tth_s after the decomposed segment is iterated thoroughly, the local-minimum is also considered a TA candidate.

As described previously, the TA occurs on the position with local minimum in the breath signal. Thus the previously described approach basically performs TA detection based on the u(or v) shaped local-minimum along with some extending features after the local u(or v) shape feature. Despite of the adoption of extending features it was still found that noise interferences often cause significant amount of false positive detection. Thus how to further reduce the false positive has become one critical issue after the TA candidate selection. In this paper, a multilayer perceptron neural network was adopted for further selecting the TAs from the TA candidates in order to reduce the false positive.

IV. MULTILAYER PERCEPTRON FOR THE RECOGNITION OF TAS FROM TA CANDIDATES

In this section, the multilayer perceptron neural network is proposed for the recognition of trigger asynchrony from the TA candidates selected in the previous section. This multilayer perceptron neural network is designed to contain 201 input nodes, 20 hidden nodes and one output node, as shown in Fig. 4, used to indicate whether the input data is TA segment or not. The TA candidate selection method mentioned in the previous section will identify the point where the TA is likely to locate. These positions represent the points where u(or v) shaped local minimum is detected. With this point as the center, a period of 2 second samples in the original breath signal, which contains 201 data points, are extracted and used as the inputs to the multilayer neural network for classification. The batch mode of training is adopted. The transfer function of the hidden layer neurons and the output layer neuron is the Hyperbolic tangent sigmoid transfer function:

$$y=\frac{2}{1+e^{-2x}}-1 \quad (2)$$

where y is the output, x is the input. It's mathematically equivalent to tanh(x).

Since the TA candidate selection method selects the candidates which has local minimum, it is found that the candidate selection usually obtains extra positive data rather than misses data. It was also found that if the neural network based TA recognition is applied on all the breath cycle, namely all of data without pre-selection, the complexity of the data would cause the degradation of the network performance. Based on this consider, it is designed that the neural network is targeted for TA recognition among the TA candidates.

In order to properly capture the property that the network makes the recognition following TA candidate selection, the training of the neural network is performed also on the candidate data. As such both TA and non-TA training samples were obtained from the results of the candidate selection. One of the benefits for this approach is that the TA detection can then be divided into domain reduction followed by the recognition. The TA candidate selection method chooses the candidates in order to reduce the classification domain into more narrow region. Thus when the process is in the classification phase by neural network, the data consistency is increased and variation is reduced. Thus it is expected to achieve a higher recognition rate.

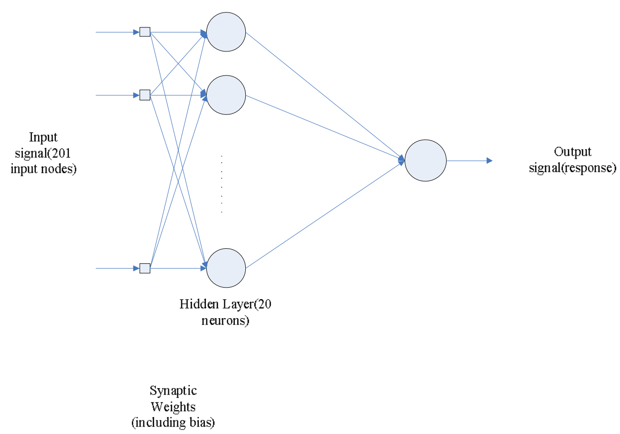

Fig 4. The two layer perceptron neural network for TA recognition from candidates.

Based on these descriptions, the data of true positive and false positive from the candidate selection are sampled for training the network. The ground truth is obtained based on esophageal pressure, where a true TA would cause the esophageal pressure to drop about 1 cmHg. On the other hand, noise caused signal variation would not involve the drop in esophageal pressure. Thus if a TA candidate does not has the characterstic of the esophageal pressure drop larger than or equal to 1cmHg, this data would be considered a negative case for the network training.

In order to evaluate the effect to classification performance when different training approaches and different threshold values are applied in the candidate selection, several experiments are conducted on the network training. In all of the experiments, the following parameter values are adopted: th_s=3(cm-Hg), th_f=0.5(cm-Hg) and θ_L=1.2.

(1) Dual-d_5-2times-den-insp_asym: In this test, two MLPs is used, one for the recognition of the inspiratory TA and the other for the recognition of expiratory TA. The training set for the neural network for inspiratory phase is asymmetric. That is, the number of non-TA examples for training the neural network is about two times the number of TA examples, considering that the TA candidates contain more non-TA than true TA in inspiratory phase. On the other hand, the network for expiratory phase has symmetric training samples. In other words, about the same number of non-TA and TA data samples are used for training. In this experiment d_5 decomposition is used for candidate selection and tth_s=2, tth_f=2.

(2) Dual-d_5-1time-den: In this test, two MLPs are used where one is for inspiratory phase and the other is for expiratory phase. In this experiment, both networks use symmetric data training, that is, the same numbers of non-TA and TA samples are used for both inspiratory and expiratory neural networks. Also, d_5 decomposition is used for candidate selection and tth_s=2, tth_f=2.

(3) Dual-d_6-1time-den-insp_asym:This experiment has similar condition as the situation in (1). That is, two MLPs are used for inspiratory phase and expiratory phase. Asymmetric data were used for training the network for inspiratory TA recognition, and symmetric for expiratory TA recognition. The only difference is that d_6 decomposition of DWT is used, tth_s=1 and tth_f=1.

(4) Single-d_6-2times:

This experiment uses one MLP for the recognition of TA. As such, the samples from the inspiratory phase and expiratory phase are adopted for the training. Also, symmetric data are used for training and d_6 decomposition of DWT is used. tth_s=2, tth_f=2. De-noising is not used.

(5) Single-d_5-2times:

This experiment has the same condition as that in (4) except that d_5 decomposition of DWT is used. Also tth_s=2 and tth_f=2.

V. EXPERIMENTAL RESULTS AND DISCUSSIONS

For testing the proposed approach, 7 breath sequences collected with airway pressure and airway flow were used for the test. Each breath sequence has more than 1000 seconds of length. In order to better understand the situation of candidate selection, Table II, and III illustrate the results of three expiratory breath sequences after the TA candidate selection phase without applying the de-noising algorithm. The TA candidates selected here are treated as TA. The results listed in these tables include:

(1) Correct expiratory segment type 1(CES1): Each expiratory segment may contain several TA points. In this evaluation, if the number of detected TAs matches the number of true TAs, this segment is considered a correctly detected expiratory segment type 1(CES1).

(2) Classification rate type 1(CR1): This is defined as the number of correctly detected expiratory segments (CES1) divided by the total number of expiratory segments.

(3) True positive TA (TP): This is defined as the true positive of TA. That is, the number of detected TA candidates which are TAs.

(4) True positive rate(TPR): This is defined to be the true positive TA divided by the total number of TAs.

(5) False positive TA(FP): This is defined as the false positive TA. That is, the number of detected TA candidates which are not TAs.

(6) TA Misrecognition rate (TAMR): This is defined as the number of false positive TA divided by the total number of segments.

From the results, we can see that if the value of θ_L increases, the true positive decreases. It also shows the relatively high false positive (FP) on all the situations. In order to maintain a significant high value of true positive, the θ_L for our candidate selection is set to be 1.2 for selecting the candidate TAs for further recognition in the neural network stage.

Based on these results, the θ_L is set to be 1.2 in the candidate TA selection for higher true positive and not including too much false positive. The candidates selected are then fed to the neural network for classification. The results after neural network classification for 6 breath sequences are shown in Table V, where each row lists the result for a breath sequence, and the last row gives the average results. Within each row there are 6 sub-rows, where the first 5 sub-rows give the results for the 5 test methods with different parameter sets as described in the previous section, namely,

(1) Dual-d_5-2times-den-insp_asym.

(2) Dual-d_5-1time-den.

(3) Dual-d_6-1time-den-insp_asym.

(4) Single-d_6-2times.

(5) Single-d_5-2times.

For comparison, the last sub-row lists the results by experienced therapist's observation for TA detection. The results listed in Table V include:

(1) File name (FN): Simplified File Name.

(2) Number of Segments(S).

(3) Classification rate (CR): This is defined as the number of correct segments (CS) divided by the total number of segments. In the evaluation, only if all the detected TA positions in a segment are within 1 second from the true TA positions and there is no false positive TA in this segment, this segment is considered a correct segment.

(4) Correct segments comparing ratio (CSCR) which is defined as the number of correctly detected segment by our approach divided by the number of correctly detected segment by doctor or therapist observation,

(5) True positive rate(TPR): as described before.

(6) True positive comparing ratio(TPCR), which is the true positive rate by this approach divided by the true positive rate by therapist observance.

(7) TA Misrecognition rate(TAMR): as defined above.

(8) TA misrecognition comparing ratio(TAMCR): This is the TA Misrecognition rate (TAMR) by experienced therapist observance divided by the TAMR by this approach.

(9) Avg.: Average data.

Table II
The expiratory phase TA recognition result of file TANEW8(N8) with 12 expiratory TAs and 915 expiratory segments.

θ_L	CES1	CR1	TP	TPR	FP	TAMR
1.2	715	78.14%	8	66.67%	245	13.01%
1.5	760	83.06%	8	66.67%	174	13.01%
1.8	802	87.65%	8	66.67%	119	13.01%
2.1	834	91.15%	8	66.67%	82	8.96%
2.4	852	93.11%	7	58.33%	62	6.78%
2.7	860	93.99%	5	41.67%	51	5.57%

Table III
The expiratory phase TA recognition result of file TANEW16(N16) with 161 TAs and 932 expiratory segments.

θ_L	CES1	CR1	TP	TPR	FP	TAMR
1.2	504	54.08%	135	83.85%	459	49.25%
1.5	543	58.26%	125	77.64%	390	41.85%
1.8	574	61.59%	119	73.91%	351	37.66%
2.1	605	64.91%	105	65.22%	301	32.30%
2.4	619	66.42%	95	59.01%	274	29.40%
2.7	652	69.96%	87	54.04%	230	24.68%

By referring to Table IV, the result of mode --Dual-d_5-den-insp_asym which uses two neural networks for inspiratory and phase and expiratory phases recognition, d_5 decomposition of DWT-- has the best and the most balanced performance comparing with the therapist observation results. In this situation the proposed approach reveals 100.75% CSCR, 72.68% TPCR, and 407.10% TAMCR. However if we would like to obtain better TPCR, the Dual-d_5-1time-den with 85.37% may be chosen.

From the results, we can also see the result variation for different patients or different situations. This is due to that these patients are in different ventilators and therefore may

Table IV
Test result of the algorithm with 6 breath sequence data files.

FN	CR	CSCR	TPR	TPCR	TAMR	TAMCR
11 (6TAs, 1158S, Patient A)	99.22%	99.91%	16.67%	∞	0.52%	150.00%
	99.74%	100.43%	0.00%	100.00%	0.43%	180.00%
	94.47%	95.13%	0.00%	100.00%	5.01%	15.52%
	93.78%	94.43%	16.67%	∞	6.39%	12.16%
	97.58%	98.26%	0.00%	100.00%	2.50%	31.03%
	99.31%	–	0.00%	–	0.78%	–
N3 (1TA, 537S, Patient B)	96.83%	97.93%	100.00%	100.00%	4.84%	7.69%
	62.94%	63.65%	100.00%	100.00%	55.12%	0.68%
	99.07%	100.19%	100.00%	100.00%	0.37%	100.00%
	63.13%	63.84%	100.00%	100.00%	47.30%	0.79%
	75.05%	75.89%	100.00%	100.00%	29.98%	1.24%
	98.88%	–	100.00%	–	0.37%	–
N8 (17TA, 1839S, Patient C)	98.91%	103.06%	11.76%	33.33%	1.71%	231.47%
	98.04%	102.15%	29.41%	83.33%	1.31%	304.17%
	97.61%	101.70%	17.65%	50.00%	1.31%	303.01%
	97.61%	101.70%	23.53%	66.67%	1.74%	228.13%
	96.36%	100.40%	23.53%	66.67%	2.78%	142.59%
	95.98%	–	35.29%	–	3.97%	–
N13 (228TA, 1504S, Patient D, no Tracheostomy)	92.82%	95.29%	57.46%	69.68%	1.00%	360.00%
	92.75%	95.22%	58.33%	70.74%	1.00%	360.00%
	89.16%	91.54%	18.86%	22.87%	2.79%	128.57%
	87.03%	89.35%	41.23%	50.00%	8.44%	42.52%
	90.82%	93.24%	47.81%	57.98%	7.71%	46.55%
	97.41%	–	82.46%	–	3.59%	–
N20 (74TA, 2728S, Patient E)	95.05%	103.76%	18.92%	175.00%	2.86%	702.56%
	88.67%	96.80%	44.59%	412.50%	16.94%	118.61%
	96.44%	105.28%	5.41%	50.00%	1.06%	1889.66%
	91.09%	99.44%	9.46%	87.50%	7.07%	283.94%
	86.58%	94.52%	39.19%	362.50%	12.61%	159.30%
	91.61%	–	10.81%	–	20.09%	–
N21 (19TA, 852S, Patient D, Tracheostomy)	97.42%	99.40%	0.00%	0.00%	1.41%	16.67%
	96.36%	98.32%	15.79%	100.00%	2.11%	11.11%
	96.60%	98.56%	0.00%	0.00%	1.06%	22.22%
	93.43%	95.33%	0.00%	0.00%	4.34%	5.41%
	96.01%	97.96%	10.53%	100.00%	2.82%	8.33%
	98.00%	–	10.53%	–	0.23%	–
Avg. (326TAs, 7766S)	96.39%	100.75%	43.19%	72.68%	1.96%	407.10%
	92.03%	96.19%	50.72%	85.37%	9.51%	83.90%
	95.34%	99.65%	14.78%	24.88%	1.90%	419.51%
	90.62%	94.72%	31.01%	52.20%	8.32%	95.96%
	91.10%	95.22%	42.03%	70.73%	8.41%	94.90%
	95.67%	–	59.42%	–	7.98%	–

have different TA width and depth. However, generally speaking, the algorithm provides satisfactory results for most breath sequences, compared with the therapist performance.

The following is a comparison of Dual-d_5-den-insp_asym (mode 1) and Dual-d_5-1time-den(mode 2): mode 1 has lower true positive rate (TPR) since it adopts asymmetrical inspiratory phase training which filters out more inspiratory phase trigger asynchrony but it also has lower false positive rate (FPR) since it filters out more inspiratory phase false positive trigger asynchrony. Due to the high FPR of mode 2, mode 1 has higher CSCR.

Mode Dual-d_6-1time-den-insp_asym(mode 3) has extremely low TPR since the d_6 decomposition has slightly lower resolution than the breath frequency bands. It filters out many lower width TAs automatically. But it also has lower FPR because it filters out many points which is not TA but similar with TA.

Mode d_6-1time inherits the low resolution of d_6 so it performs worse than mode 1 in CR, TPCR and TAMCR.

By the result and the requirement of balanced TP and FP, the mode 1 Dual-d5-den-insp_asym is suggested to be the best solution with good and balanced performance of CSCR, TPCR, TAMCR.

Different modes may reveal different performances for different breath sequences. For example, in N03, Dual-d_6-1time-den-insp_asym has better performance than Dual-d_5-den-insp_asym. That's because this sequence contains very few TAs, namely only 1 TA. Both modes correctly detect this TA, which gives the same true positive. But as d_6 has lower resolution, it generally picks less TAs from the noise, giving less false positive. As such Dual-d_6-1time-den-insp_asym has smaller TAMR 0.38% than the Dual-d_5-den-insp_asym 4.88%. This situation results from the case of very few TAs, causing insufficiency in the true positive statistic.

In the future, the more detailed statistics of the TA properties including width, depth and main frequency band shape can be explored to refine the algorithm to achieve better results.

VI. Conclusions

Trigger asynchrony is a phenomenon when the ventilator is out of synchronization with breathes of respiratory patients. The occurrence of trigger asynchrony would cause discomfort and harms to patients. In the past, TA detection is performed through doctor or therapist observance, which requires high human resources and is usually untimely. This paper explores the combination of wavelet transformation and neural networks for trigger asynchrony detection. In contrast to commonly applied signal processing approaches where the wavelet transformation is used for extracting features which are then applied to the neural networks as the input for classification, this paper uses the wavelet transformation for problem domain reduction. After that, the neural network is applied in the restricted domain for pattern classification. With this approach the feature space domain can be reduced before applied into the neural network. As such the neural network classification rate can be significantly increased compared with the situation when the domain is not restricted.

In order to give detailed comparison on the wavelet coefficients in the candidate selection efficiency, various wavelet sub-bands were selected for testing based on the main frequency component of TA phenomenon in airway pressure signal. The results were compared with the results obtained from doctor observance, the adopted approach in the past. Results also demonstrate a significant competitive performance, showing its prominence in TA detection.

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REFERENCES

[1] Dimitris Georgopoulos, George Prinianakis, Eumorfia Kondili. "Bedside waveforms interpretation as a tool to identify patient-ventilator asynchronies". Intensive Care Med 32, p.p. 34–47, 2006.

[2] David C. Chao, David J. Scheinhorn, and Meg Stearn-Hassenpflug, "Patient-Ventilator Trigger Asynchrony in Prolonged Mechanical Ventilation, Clinical Investigations in Critical Care," CHEST, Vol 112(6), p.p. 1592-1599, DECEMBER, 1997.

[3] Leung P, Jubran A and Tobin MJ. "Comparison of assisted ventilator modes on triggering, patient effort and dyspnea". Am J Respir Crit Care Med 155, p.p. 1940-1948, 1997.

[4] Stéphane Mallat, "A wavelet tour of signal processing," , second edition. Academic Press, pp. 1-19, 42-587, 1999.

[5] C. Sidney Burrus, Ramesh A. Gopinath, and Haitao Guo, "Introduction to Wavelets and Wavelet Transfroms," A Primer, p.p. 7-8, 1998.

[6] Kuan-Hui Li, Pau-Choo Chung, A Motion Emphasized 3-D SPIHT for Visual Improved Video Coding , Master Thesis of Institute of Computer & Communication Engineering in National Cheng-Kung University, pp. 7-11, August 2005.

[7] Oczeretko E, Świątecka J, Laudański T "Uterine contractility signals– an introduction to wavelet analysis," Annales Acadeenmiae Bialostocensis, Vol.48, pp. 135-140, 2003.

[8] Lan Chang, Pau-Choo Chung, Trigger asynchrony recognition embedded with home health care box, Master Thesis of Institute of Computer & Communication Engineering in National Cheng-Kung University, p.p. 14-16, August 2006.

[9] David L. Donoho, "De-Noising by Soft-Thresholding," IEEE Transactions on Information Theory, VOL.41, No. 3, pp. 613-627, May 1995.

[10] Michael F. Kelly, Philip A. Parker, and Robert N. Scott, "Myoelectric Signal Analysis Using Neural Networks", IEEE Engineering in Medicine and Biology Magazine, pp. 61-64, March 1990.

[11] Simon Haykin. "Neural Networks- a comprehensive foundation", second edition, Prentice Hall, New Jersey, U.S.A, pp. 156-251, 1999.