# VENTILATION CLASSIFICATION FOR CARDIOPULMONARY RESUSCITATION QUALITY MONITORING USING THORACIC IMPEDANCE

M. Risdal*, H. Losert**, J. Nysæther***, S. O. Aase*, F. Sterz**, and T. Eftestøl*

*University of Stavanger, Stavanger, Norway
**Department of Emergency Medicine, Medical University of Vienna, Austria
***Laerdal Medical AS, Stavanger, Norway

martin.risdal@uis.no

**Abstract: It has been suggested to expand automated external defibrillators (AED) with the ability to monitor the CPR performance non-invasively and give feedback on possible improvements online. Thoracic impedance (TI) changes are closely correlated to the lung volume changes and can be measured through the AED pads. Measurements of lung volume changes and corresponding TI changes were used to explore the performance of a theoretical feedback system. Ventilation cycles were classified as having insufficient ($\omega_1$), sufficient ($\omega_2$) or too large ($\omega_3$) amounts of air according to international guidelines for CPR ventilations. A classifier was evaluated in the task of discriminating between the classes by using TI-derived information, as a feedback system would do. If the system is tuned so that it gives correct corrective feedback on 90% of insufficient ventilations, 73% of the ventilations accepted as sufficient will truly be sufficient. The TI may give some indication on the amount of air given to the patient, but it is not advisable to use impedance measurements for feedback on tidal volume because of the low accuracy.**

## Introduction

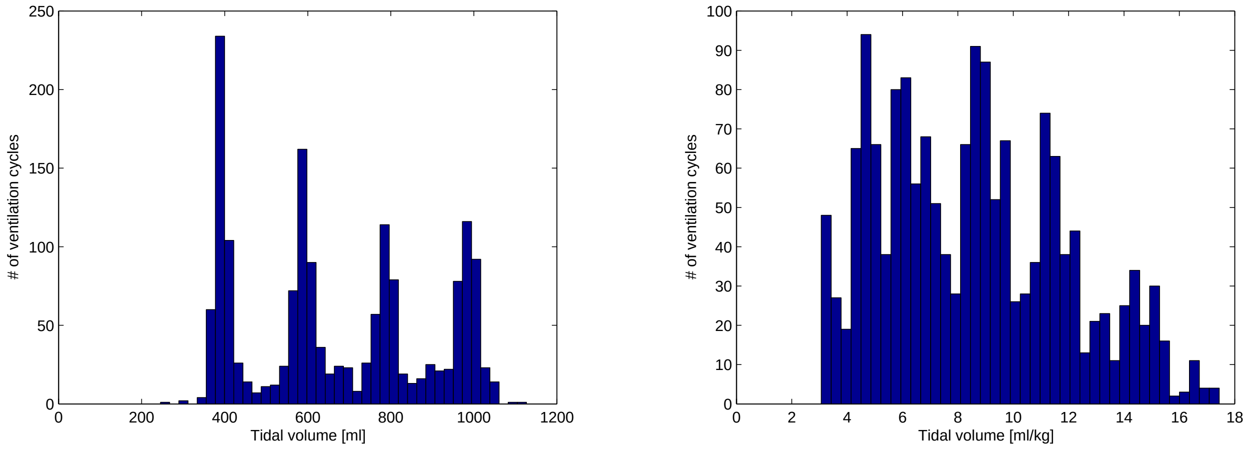
Recent publications [1, 2] concerning CPR quality has shown divergence from the recommendations of Guidelines 2000 [3]. The main problems are hyperventilations, low compression rates, too shallow compressions and long pauses in CPR [1, 2]. Aufderheide et al recently demonstrated that rescuers consistently tend to hyperventilate out of hospital cardiac arrest patients [4], and a pig model has shown that increased tidal volumes adversely affect cardiac output [5]. Other studies indicate that the quality of CPR performance influences the outcome [6, 7, 8]. To overcome the problem of suboptimal CPR, Handley et al [9] suggested to incorporate a feedback system in automated external defibrillators (AED). Transthoracic impedance (TI) changes are closely correlated to lung volume changes [10, 11, 12]. During inspiration, TI increases, while it decreases during expiration. By monitoring the TI by means of the self-adhesive defibrillator pads, it can be used for ventilation assessment [13]. By analyzing the impedance signal resulting from one ventilation cycle, the AED can possibly give accurate feedback on whether the ventilation is in accordance with Guidelines. We wish to investigate the potential of using the impedance signal for feedback on ventilation volume.

The relationship between inspired amount of air and resulting impedance change is dependent on body composition and therefore varies between patients [12]. In a cardiac arrest situation there are no possibilities for calibration of the monitoring equipment to fit the patient's physiology, at the cost of lowered accuracy in the feedback. In this paper we look at the performance and accuracy of such a ventilation feedback system using a pattern recognition framework. The task of the framework is to classify ventilations based on impedance measurements.

We first present the data material used in our experiments. The classification problem is then presented, followed by a description of the discriminating features to be extracted from the data. We then present the framework used for evaluating the classifier's discriminating power. The results are presented, followed by a discussion and a conclusion of our work.

## Materials and Methods

The study procedures were in accordance with the ethical standards of the responsible committee on human experimentation. Data was collected from 32 patients (23 male, median age of 50, interquartile age 44-59) in hemodynamically stable controlled mechanical ventilated conditions at the University Clinic of Vienna municipal hospital. Weight ranged from 50 to 120 kg (median 76, interquartile weight 65-89.5).




(a) (b)

Figure 1: The tidal volume distribution of the data set in (a) ml and (b) ml/kg.

All patients were ventilated with a ServoI® Ventilator system (Version1.2, Siemens Medical Group, Frankfurt, Germany), which also continuously measured the respiratory volume. Sampling rate was 100 Hz and dynamic range was 16 bits. The resolution was 0.1 ml/bit. An investigational monitor/defibrillator, based on a commercially available monitor/defibrillator (Heartstart®4000SP, Laerdal Medical, Stavanger, Norway) was used for the impedance measurements in the study . A 32 kHz sinusoidal excitation current, 3mA peak-to-peak, was applied between the defibrillation pads, and the resulting impedance was registered. The resolution of the defibrillator impedance measurement system was 0.74 mΩ/bit. Sampling rate was 500 Hz and dynamic range was 16 bits. The impedance measurements were downsampled to 100 Hz to be compatible with the volume measurements. Heartstart®4000SP with the necessary analysis software were provided by Laerdal Medical. The thorax impedance measurements were recorded using commercially available self-adhesive electrode defibrillator pads (Heartstart Pads®, Philips Medical Systems, Seattle, WA, USA). A low pass equiripple FIR filter was used off-line for noise and cardiogenic artifact reduction in the impedance signal.

For each patient, the measurements were performed for tidal volumes of 400, 600, 800 and 1000 ml, each for 2 minutes. The tidal volume (TV) is the amount of air inhaled and exhaled during one respiratory cycle, i.e. peak inspired volume for a given respiratory cycle. 6 of the patients were not ventilated at 800 ml due to changes of experimental protocol, and the measurements at 1000 ml were corrupted during transfer for one patient. 3 patients were excluded because of no ventilations with TV of 800 and 1000 ml. For each patient, 15 respiration cycles for each TV were used for training and testing of the classifier. The true range of the TVs, after analysis of the collected data, were 300 ml to 1100 ml. This was due to transients when readjusting the TV delivered by the ventilator. The TV distribution of the data set are presented as histograms in Figure 1. Figure 1(a) shows the distribution of the ventilations in ml and Figure 1(b) shows the distribution in ml/kg.

Table 1: CPR Ventilation Guidelines.

| | Recommended tidal volumes | Inflation time, non-secure airway |
|---|---|---|
| Mouth-to-mouth ventilation | approx. 10 ml/kg or 700-1000 ml | 2 sec |
| Bag-valve-mask ventilation, with oxygen | approx. 6-7 ml/kg or 400-600 ml | 1-2 sec |
| Bag-valve-mask ventilation, without oxygen | approx. 10 ml/kg or 700-1000 ml | 2 sec |

Table 2: Classifier definitions and class distribution of the 1530 ventilations.

| | $\omega_1$ | $\omega_2$ | $\omega_3$ |
|---|---|---|---|
| | TV $<$ 6 ml/kg AND TV $<$ 400 ml | TV $>$ 6 ml/kg OR TV $>$ 400 ml AND TV $<$ 1000 ml | TV $>$ 1000ml |
| # of elements | 277 | 1271 | 102 |

The recommendations for performing CPR ventilations are stipulated in [14], and are listed in Table 1. Based on these criteria, we define three classes. A ventilation belonging to class $\omega_1$ is a ventilation with TV below the CPR guidelines, that is below 400 ml and below 6 ml/kg. If the TV of a ventilation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is above the guidelines (TV> 1000 ml), it belongs to class $\omega_3$. Otherwise the TV is sufficient, and the ventilation belongs to $\omega_2$. The definitions of the three classes for the classifier are shown in Table 2, along with the number of elements in each class.

The performance of a classifier can be evaluated and visualized by means of Receiver Operating Characteristics (ROC) graphs [15]. The area under the ROC curve, AUC, is used as a measure of performance, but this technique is only applicable to the case of two classes. A method for using ROC curves in the evaluation of multiple class classifiers was proposed in [16]. The multiple class problem is divided in all possible two-class problems, and the overall performance, $\text{AUC}_{total}$, is the mean AUC of the two-class problems. This is expressed as

$$\text{AUC}_{total} = \frac{2}{c(c-1)} \sum_{i<j} \text{AUC}_{i,j} \tag{1}$$

where $c$ is the total number of classes and $\text{AUC}_{i,j}$ is the area under the ROC curve when discriminating between elements from class $\omega_i$ and $\omega_j$.

We now identify the features that are to represent the impedance measurement of each respiration cycle. The assumed most important discriminating feature for the classification problem is the TI change, denoted $dZ$, from start of ventilation to top of ventilation. Because of the varying relation between respiration and impedance change between patients [10, 11], this does not give exact information on the TV. For a TV of 400 ml, the resulting impedance change might vary from 0.3 to 1.1 Ω depending on the patient. We therefore need other features that can help improve the classifier.

Studies of the respiration curve normalized so that the maximum amplitude equals 1 indicate that the expiration curve may contain information related to the TV. It is observed that the expiration curve has a slower decline for ventilations with high TV than for low TV, with TV expressed in ml. This is illustrated in Figure 2.One way of exploiting this is by performing polynomial regression, and use the polynomial coefficients to represent the expiration curve in the feature space. The goal is a good representation of the curve's shape while keeping the number of coefficients low, and thereby containing the discriminating information in as few parameters as possible. We let $\mathbf{x} = [x_1, x_2, ..., x_N]^T$ represent the normalized expiration curve, and let $\mathbf{t} = [t_1, t_2, ..., t_N]^T$ represent the time instants of $\mathbf{x}$ and where $t_1 = 0$. $N$ is the number of samples. The polynomial of order $P$ that best fits $\mathbf{x}$ in a least squares sense can then be found by solving

$$\mathbf{Ta} = \mathbf{x} \tag{2}$$

where $\mathbf{T}$ is a $P \times N$ matrix with $\mathbf{t}^{(p-1)} = [t_1^{(p-1)}, t_2^{(p-1)}, ..., t_N^{(p-1)}]^T$ as the p'th column, and $\mathbf{a} = [a_0, a_1, ..., a_{P-1}]^T$ is vector consisting of the polynomial coefficients. We let $b_0$ and $b_1$ represent the coefficients of a 1. order polynomial found as described in Eq. (2). $b_0$ and $b_1$ are used as features in the classification.

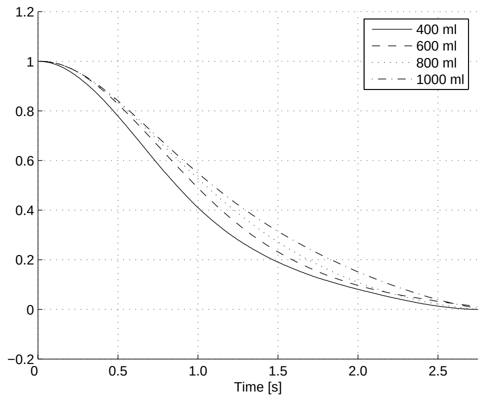


Figure 2: The expiration curve shape dependence on the tidal volume.

A time-normalized version of $\mathbf{x}$ may also be used in the same way. The signal is then resampled to a duration of 1 second, where the resampling factor is given by

$$R = \frac{N_{new}}{N_{old}} \tag{3}$$

$N_{old}$ and $N_{new}$ is the number of samples representing the expiration curve before and after resampling. Polynomial regression can also be performed on the resampled expiration curve and give new features. The features $c_0$, $c_1$, $c_2$, $c_3$, $d_0$ and $d_1$, representing the coefficients of a 3. and 1. order polynomial found as described in Eq. (2) of the resampled expiration curve, are used in the classification.

From Figure 2 it is seen that higher TV leads to longer duration, and thereby higher energy spread, of the expiration curve. In [17] an energy measure of the signal length is referenced. It relates how the energy of the signal is distributed over its duration. The general definition of the energy measure, denoted $SL$, is

$$SL = \frac{\sum_{n=0}^{N-1} w(n) \cdot x^2(n)}{\sum_{n=0}^{N-1} x^2(n)} \tag{4}$$

where $x(n)$ is the signal and $w(n)$ is a non-decreasing, positive weighting function with $w(0) = 0$. We use $w(n) = n$, and use $SL$ in the classification.

We now have many possible ways of combining the proposed features, but it is desirable to minimize the number of feature combinations before presenting the data to the classifier. Many methods have been proposed to determine the best subset [18]. We use the approach of examining the feature space $\mathbf{V}$ spanned by the extracted features $\mathbf{v}$, and evaluate how separable the given classes seem to be. This is done by relating the variance within the classes to the distances between the class centers. The mean-squared within-class distance $V_i^2$ between samples $\mathbf{v}$


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Table 3: Classifier performance represented by the mean (standard deviation) AUC.

| Features | $\text{AUC}_{total}$ | $h1$ | $\text{AUC}_{1,2}$ | $h1$ | $\text{AUC}_{1,3}$ | $h1$ | $\text{AUC}_{2,3}$ | $h1$ |
|---|---|---|---|---|---|---|---|---|
| $\mathbf{v}_1 = [dZ]$ | 0.869 (0.062) | 1.7 | 0.868 (0.063) | 1.2 | 0.981 (0.058) | 1.7 | 0.783 (0.132) | 1.5 |
| $\mathbf{v}_2 = [dZ, SL, b_0, b_1]$ | 0.876 (0.058) | 2.0 | 0.871 (0.052) | 1.2 | 0.984 (0.041) | 2.0 | 0.776 (0.123) | 2.0 |
| $\mathbf{v}_3 = [dZ, SL]$ | 0.889 (0.049) | 2.0 | 0.861 (0.049) | 2.0 | 0.992 (0.019) | 2.0 | 0.813 (0.110) | 2.0 |
| $\mathbf{v}_4 = [dZ, c_0, c_1, c_2, c_3]$ | 0.858 (0.071) | 1.9 | 0.865 (0.056) | 1.7 | 0.973 (0.061) | 1.9 | 0.726 (0.148) | 1.9 |
| $\mathbf{v}_5 = [dZ, SL, c_0, c_1, c_2, c_3]$ | - (-) | - | 0.866 (0.055) | 1.9 | 0.988 (0.028) | 1.5 | - (-) | - |
| $\mathbf{v}_6 = [dZ, d_0, d_1]$ | 0.880 (0.064) | 2.0 | 0.869 (0.082) | 1.8 | 0.986 (0.048) | 2.0 | 0.787 (0.121) | 2.0 |
| $\mathbf{v}_7 = [dZ, SL, d_0, d_1]$ | 0.872 (0.052) | 1.7 | 0.877 (0.042) | 1.7 | 0.992 (0.018) | 1.8 | 0.752 (0.131) | 1.7 |
| $\mathbf{v}_8 = [dZ, d_0, d_1, R]$ | 0.861 (0.078) | 2.0 | 0.860 (0.052) | 1.1 | 0.983 (0.052) | 1.5 | 0.764 (0.126) | 1.8 |
| $\mathbf{v}_9 = [dZ, SL, d_0, d_1, R]$ | 0.852 (0.054) | 1.9 | 0.872 (0.060) | 1.9 | 0.981 (0.044) | 1.9 | - (-) | - |
| $\mathbf{v}_{10} = [dZ, R]$ | 0.867 (0.062) | 1.7 | 0.863 (0.058) | 1.7 | 0.980 (0.053) | 1.7 | 0.777 (0.132) | 1.0 |

of class $i$ and the corresponding class mean $\mu_i$ is

$$V_i^2 = E\{|\mathbf{v} - \mu|^2 | i\} = var\{\mathbf{v}|i\} = trace[\mathbf{\Sigma_i}]. \quad (5)$$

The mean of these within-class squared distances $V^2$, when assuming equiprobable classes, is

$$V^2 = \frac{1}{c}\sum_{i=1}^{c} V_i^2. \quad (6)$$

The mean-squared between-class distance, denoted $D^2$, for equiprobable classes is

$$D^2 = \frac{1}{c(c-1)}\sum_{i=1}^{c}\sum_{j=1}^{c}|\mu_i - \mu_j|^2 \quad (7)$$

A measure of separability is then derived as the ratio

$$Q = \frac{V^2}{V^2 + D^2} \qquad 0 \le Q \le 1 \quad (8)$$

ranging from 0 to 1. $Q \to 0$ indicates optimum separability, while $Q \to 1$ indicates inseparability. This value is computed for a number of feature combinations, and the best ones are used in the training and testing of the classifiers. Using the proposed classes and features, we want to evaluate how well a classifier will discriminate between the classes. The most important discriminating feature is according to the results $dZ$. Since the relationship between TV and $dZ$ is patient-dependent, so is the performance of a classifier. The training and test set is therefore divided patient-wise, and cross-validation [15] is performed. 5 randomly selected patients are in the test group and the remaining 21 patients are in the training group. It is assured that every patient is represented in the test data at least twice, so we end up with 52 training and test sets.

The Parzen window technique [15] is used to estimate the class dependent probability $p(\mathbf{v}|\omega_j)$ of all the ventilations for each of the three classes. It is computed as an average of normal densities centered at the samples:

$$p(\mathbf{v}|\omega_j) = \frac{\sqrt{n_i}}{n_i}\sum_{n=1}^{n_i}\frac{1}{\sqrt{2\pi h_1^2}}e^{-\frac{n_i}{2h_1^2}(\mathbf{v}-\mathbf{v}_n)^2} \quad (9)$$

Here $n_i$ is the size of the training set of class $\omega_i$. The window size $h1$ should be adjusted so that good generality is achieved, that is

$$|M_{\text{test set}} - M_{\text{training set}}| < \tau \quad (10)$$

where $M_{\text{test set}}$ and $M_{\text{training set}}$ is some chosen measure (in our case AUC) of the classifier's performance on the test and training set. For our setup we use $\tau = 0.05$, and calculate the performance of the classifier for $h1 \in \{1.0, 1.1, ..., 2.0\}$.

As proposed in [16] the original 3-class problem is divided in three 2-class problems. Bayes decision rule for minimizing the overall risk for a two-category classification problem is to decide $\omega_i$ if

$$(\lambda_{ji} - \lambda_{ii})p(\mathbf{v}|\omega_i)P(\omega_i) > (\lambda_{ij} - \lambda_{jj})p(\mathbf{v}|\omega_j)P(\omega_j) \quad (11)$$

and otherwise decide $\omega_j$ [15]. $P(\omega i)$ is the a priori probability of $\mathbf{v} \in w_i$. $\lambda_{ij}$ is the cost of deciding that $\mathbf{v} \in \omega_i$, when in fact $\mathbf{v} \in \omega_j$. By adjusting the costs, we can get $(\lambda_{ji} - \lambda_{ii})P(\omega_i)$ and $(\lambda_{ij} - \lambda_{jj})P(\omega_j)$ to assume any value we want. We let $(\lambda_{ji} - \lambda_{ii})P(\omega_i) = c_i$ and $(\lambda_{ij} - \lambda_{jj})P(\omega_j) = c_j$, and reformulate the decision rule to decide $\omega_i$ if

$$c_i \cdot p(\mathbf{v}|\omega_i) > c_j \cdot p(\mathbf{v}|\omega_j) \quad (12)$$

and otherwise decide $\omega_j$. For a choice of $c_i$ and $c_j$ we can now calculate the sensitivity and specificity of our training and test set, expressed as [17]

$$\text{sensitivity}_i = \frac{\#\text{ of correct classifications where } \mathbf{v} \in \omega_i}{n_i} \quad (13)$$

and

$$\text{specificity}_i = \frac{\#\text{ of correct classifications where } \mathbf{v} \notin \omega_i}{\sum_{j \ne i} n_j}, \quad (14)$$

where $n_i$ is the number of elements belonging to class $\omega_i$, and thereby points in the ROC graph. We use $c_i + c_j = 1$ and $c_i \in \{0, 0.001, 0.002, \ldots, 0.999, 1\}$ to ease implementation in computation of the ROC graphs. The area under the ROC graph, $\text{AUC}_{i,j}$, can then be calculated for the training and the test set, and give a general measure of the classifier's performance.

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Table 4: Significance level of the Kruskal-Wallis hypothesis test when comparing $\text{AUC}_{i,j}$ of $\mathbf{v}_1$ with other feature combinations for the classifier.

| Features | $\omega_1$ vs. $\omega_2$ | $\omega_1$ vs. $\omega_3$ | $\omega_2$ vs. $\omega_3$ |
|---|---|---|---|
| $\mathbf{v}_2$ | 0.816 | 0.535 | 0.551 |
| $\mathbf{v}_3$ | 0.467 | 0.652 | 0.233 |
| $\mathbf{v}_4$ | 0.968 | 0.892 | 0.078 |
| $\mathbf{v}_5$ | 0.894 | 0.972 | - |
| $\mathbf{v}_6$ | 0.373 | 0.052 | 0.991 |
| $\mathbf{v}_7$ | 0.492 | 0.848 | 0.175 |
| $\mathbf{v}_8$ | 0.415 | 0.351 | 0.419 |
| $\mathbf{v}_9$ | 0.710 | 0.583 | - |
| $\mathbf{v}_{10}$ | 0.749 | 0.762 | 0.871 |

For each classifier, we now have performance measure distributions for $\text{AUC}_{1,2}$, $\text{AUC}_{1,3}$, $\text{AUC}_{2,3}$ and $\text{AUC}_{\text{total}}$. The distributions of the results for the different classifiers are compared by using a Kruskal-Wallis nonparametric one-way ANOVA hypothesis test [19] to see if there are any improvements in discriminative power when using expiration curve information.

A better impression of the classifier's accuracy when used in a clinical setting is found by choosing a specific working point on the ROC graph, and thereby a specific sensitivity and specificity. Again we look at the three 2-class problems separately. We demand a sensitivity $> 90\%$, which means that the AED should for example correctly ask for more air 90 % of the time when the patient is ventilated insufficiently. The resulting specificity will then for the same example give an impression of how often the feedback system is correctly not asking for more air.

## Results

After calculating the separability of a vast number of feature combinations using Eq. (8), ten feature combinations were used in the classifier evaluation. They are presented in the first column in Table 3. The best discriminative ability in terms of AUC of the classifier while using a $h1$ that gives good generality is presented in Table 3. The window width $h1$ used for achieving the results are also listed. Some of the feature combinations did not meet the demand of generality for any of the tested window widths, and the results are therefore not displayed. $\mathbf{v}_3$ is the feature with best discriminative ability for all categories except for when discriminating between $\omega_1$ and $\omega_2$. Here $\mathbf{v}_7$ achieves the best results.

We then used the Kruskal-Wallis hypothesis test to test if there was a significant improvement in using features describing the expiration curve of the ventilation. The results are presented in Table 4, and we observe that there is no significant increase in discriminative power of the classifier from representing the expiration curve. The specificity

Table 5: Classifier performance in terms of mean (standard deviation) specificity when demanding a mean sensitivity above 90%.

| Features | $\omega_1$ vs. $\omega_2$ | $\omega_1$ vs. $\omega_3$ | $\omega_2$ vs. $\omega_3$ |
|---|---|---|---|
| $\mathbf{v}_1$ | 0.699 (0.130) | 0.938 (0.173) | 0.325 (0.270) |
| $\mathbf{v}_2$ | 0.671 (0.121) | 0.936 (0.172) | 0.395 (0.273) |
| $\mathbf{v}_3$ | 0.694 (0.124) | 0.967 (0.118) | 0.383 (0.229) |
| $\mathbf{v}_4$ | 0.701 (0.118) | 0.909 (0.185) | 0.343 (0.246) |
| $\mathbf{v}_5$ | 0.679 (0.130) | 0.946 (0.123) | - (-) |
| $\mathbf{v}_6$ | 0.731 (0.126) | 0.973 (0.098) | 0.396 (0.270) |
| $\mathbf{v}_7$ | 0.688 (0.115) | 0.976 (0.087) | 0.310 (0.217) |
| $\mathbf{v}_8$ | 0.709 (0.088) | 0.945 (0.155) | 0.345 (0.201) |
| $\mathbf{v}_9$ | 0.704 (0.123) | 0.924 (0.180) | - (-) |
| $\mathbf{v}_{10}$ | 0.690 (0.137) | 0.930 (0.173) | 0.398 (0.274) |

of the classifier when demanding a sensitivity $> 90$ % is presented in Table 5. The same window width as presented in Table 3 is used for the different feature vectors. The use of $\mathbf{v}_6$ and $\mathbf{v}_8$ gives better specificity than if using $\mathbf{v}_1$, which shows a potential benefit of using expiration curve information. The third column shows that there is a possibility for the system to ask for less air when in fact the patient is ventilated insufficiently.

## Discussion

The need for solutions that may help improve the quality of CPR is evident from the findings in a number of studies [1, 2, 4, 6, 7, 8]. It has been suggested to equip AEDs with the ability to continuously monitor ongoing CPR, and give corrective feedback to the rescuer when necessary [20, 13]. Thorax impedance has long been used for respiration monitoring [10, 11, 21], and can easily be measured through the defibrillator pads [13]. By using simultaneous measurements of volume and impedance, we sought to evaluate the theoretical performance of a tidal volume feedback system based on impedance measured by an AED through defibrillator pads. The feedback system was to state whether the TV of a ventilation cycle was too low (class $\omega_1$), sufficient (class $\omega_2$), or to high (class $\omega_1$) according to resuscitation guidelines [14]. A classifier is designed to simulate the feedback system, where its ability to discriminate between the types of ventilations is evaluated and measured in AUC [16].

The classifier achieved mean (standard deviation) AUC of 0.877 (0.042) when discriminating between $\omega_1$ and $\omega_2$, 0.992 (0.018) when discriminating between $\omega_1$ and $\omega_3$, and 0.813 (0.109) when discriminating between $\omega_2$ and $\omega_3$ for the best feature combination. The results showed that there was a small improvement in performance when characterizing the expiration curve of the ventilation cycle. The results of the statistical testing presented in table 4 does however show that the improvement was


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not significant.

Despite the promising gain of using expiration curve characterization, the technique may possibly not be useable in a CPR setting. The data used in evaluation of the classifier were collected from mechanically ventilated and therefore intubated patients. Because of the intubation and thereby use of an endotracheal tube, the arial compliance of the trachea is different than from a setting with out intubation. The effect of the endotracheal tube on the expiration curve is unknown. Another problem is that the impedance trace is sensitive to movement. If administering series of 15 compressions and 2 ventilations, medical personnel normally starts compressions immediately after finishing the second inspiration and thereby corrupting the expiration curve. The theoretical increase in performance when using expiration curve characterization is small compared to the increase in implementation complexity if used in a real world setting.

It is also alarming that the system may ask for less air when the patient should receive more air. This may be confusing for the rescuer and dangerous to the patient, because the feedback system will in fact work against performing CPR according to the guidelines.

## Conclusions

Although inaccurate, the TI may give some indication on the amount of air given to the patient, and hopefully improve the quality of CPR. If the system is tuned so that it gives corrective feedback on 90% of insufficient ventilations, 73% of the ventilations accepted as sufficient will truly be sufficient. The discrimination between $\omega_2$ and $\omega_3$ is less convincing, with a specificity of 40 % when demanding a sensitivity of 90 % on ventilations classified as sufficient. This type of feedback should possibly be excluded in a realization of a feedback system. Because the relationship between TV and corresponding impedance change is patient dependent, the feedback system may give consistently correct feedback for one patient but will consistently erroneous feedback during ventilation of another patient. Other signals containing information about the patient's physiology that the AED can acquire, should be considered for improving the accuracy of the classifier. With the present results, it is not advisable to use impedance measurements for feedback on tidal volume because of the low accuracy.

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