A Neural Network Based Classification Algorithm for Asthma Using Capnography

[Extended Abstract]

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ABSTRACT
This article presents a neural network-based method to help physicians diagnose and monitor asthma and other chronic respiratory diseases. The method is based on capnography, using measurement data from a specially developed handheld device.

After proper preparation, various parameters are calculated on the capnographic curve from which healthcare professionals can conclude the condition of the patient's respiratory system.

Another purpose of using the calculated parameters is to serve as a learning base for an artificial intelligence application that can be used in the decision support of physicians. The shape of the capnogram obtained from the gas sample exhaled by the patient and thus the parameters calculated from it are different for healthy people and those with respiratory diseases.

Categories and Subject Descriptors
H.4 [**Information Systems Applications**]: Decision Support; J.3 [**Computer Applications**]: LIFE AND MEDICAL SCIENCES—*Capnography*

General Terms
Applications

Keywords
Decision support, Neural networks, Capnography

1. INTRODUCTION
Capnography is a non-invasive method for the numerical and graphical analysis of exhaled CO_2 concentration. Time-based capnography is part of routine daily patient monitoring during mechanical ventilation and anesthesia. For spontaneously breathing patients, the method has the advantage that it does not require the patient to carry out any special breathing maneuvers, the measurement is easy to perform, and therefore requires minimal cooperation. It also holds the potential for the diagnosis of obstructive airway disease, as bronchospasm severity can be quantitatively assessed [4, 6]. The feasibility of non-invasive examinations is essential in pediatrics, so it also opens up new areas of application for capnography [7, 9, 10]. Although the analysis of capnogram shape parameters is not yet a standard part of patient monitoring, it appears promising in the monitoring of chronic respiratory diseases, as it provides useful information on the pathophysiological processes of pulmonary ventilation, such as airway patency and lung recoil tendency.

In capnographic studies, the carbon dioxide content of exhaled air can be considered as a function of time or plotted against the exhaled gas volume. In the former case, we are talking about *time-based*, while in the latter case we are talking about *volumetric capnography*.

In the first part of the article, we examine the formal properties of time-based capnograms. Possible parameters describing the shape of the curve are presented. In the second part we introduce a neural network based method that uses these parameters to help physicians in diagnosing patients.

2. THE CAPNOGRAMS AND THEIR PARAMETERS

The capnogram curve plots the partial pressure of the CO_2 content of the exhaled gas against time or volume. The partial pressure of a given gas in a gas mixture is the pressure that a gas in question would create alone if it filled the available space alone. The partial pressure of CO_2 is denoted by PCO_2.

The capnogram consists of an exhalation segment and an inhalation segment. In this study we focused only on the shape indices of the exhalation section. The three phases of the exhalation segment (Phases 1-3) contain different slopes, angles and other parameters which are described in many articles and textbooks (e.g. [2, 3, 8]).

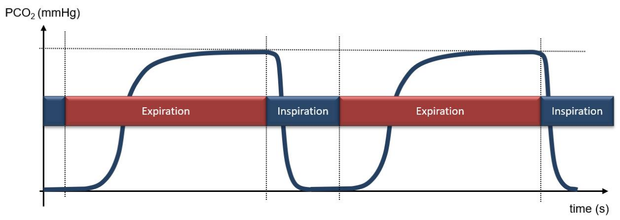

Figure 1: General form of time-based capnograms

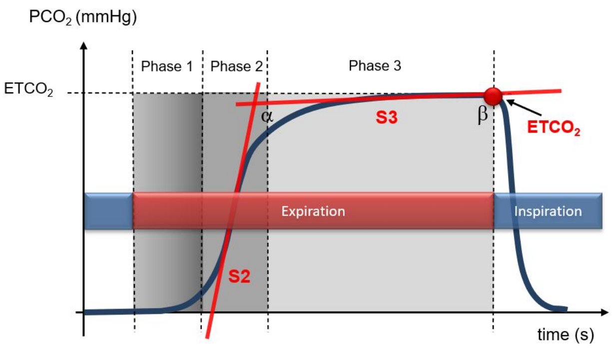

Figure 2: Phases of a capnogram with End-tidal $CO_2(ETCO_2)$

2.1 The calculated parameters

The various morphological parameters are calculated using mathematical methods, which are presented in this subsection. The resulting capnographic indices - in the knowledge of the patients' condition - provide an opportunity to assess the characteristics of healthy and chronic respiratory patients (see [12] for more details). We aim to calculate these parameters as accurately and objectively as possible. This creates the opportunity to apply learning algorithms and automatically determine the condition of the patients studied. As a first step, faulty respiratory cycles were filtered out based on physiological rules that were supported by measurement techniques.The parameter calculator smoothed the points of the raw curve using the moving average method. In this case, each point was replaced by an average calculated from a specified number of adjacent points. For the 100Hz sampling frequency used for recording, we found the 9-point moving average to be the most suitable. Then, for each point of the smoothed curve, we calculated the first-order derivatives using the standard differential quotient. Since the curve containing the first derivatives can also be slightly noisy, we performed the previous smoothing algorithm for this as well. Then, following the same method, we calculated the curve containing the second derivative and its smoothed version. Finally, using the smoothed derivative 2 curve, the starting point of Phase 2 (local maximum) and the end point of Phase 3, i.e. the end of exhalation (local minimum) can be determined. It should be noted that the starting point of the exhalation cannot be precisely determined only from the time capnogram curve. However, before the start of Phase 2, we can find the point where the curve still takes approximately a value of 0, and then this point can be considered as the starting point of the fitting algorithm described below. We then fit a function to the exhalation sections obtained as previously described using the method introduced by Tusman et al. in [11]. The beginning of Phase 2 and the end of Phase 3 have already been determined as described above, and its post-fitting correction is not necessary. However, after fitting, the first, second, and third derivatives must be re-determined (now on the fitted curve). The end point of Phase 2 (the starting point of Phase 3) is obtained from the local maximum of the calculated third derivative.

2.1.1 The slopes of Phases 2 and 3 (S2, S3)

To determine the inflection point of Phase 2, we use the first-order derivative values, which mathematically represent the slope of the line drawn at a given point on the curve. The slope at the inflection point will be the largest. The slope of Phase 2 (S2) is the maximum slope that can be read at this inflection point [11]. The slope of Phase 3 (S3) is the slope of the line fitted to the middle third of Phase 3, which is a simplified but not significantly different modification of the method used by Tusman et al [11].

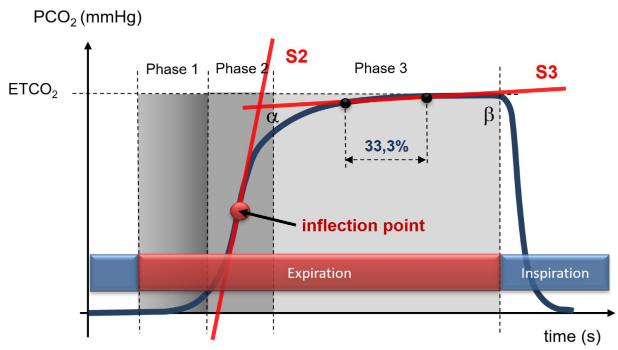

Figure 3: The slopes of time-based capnograms

2.1.2 End-tidal CO_2 ($ETCO_2$)

The carbon dioxide concentration increases throughout Phase 3, so it normally peaks at the end of the phase. This is the final exhalation CO_2 concentration ($ETCO_2$, $PETCO_2$), which is equal to the carbon dioxide partial pressure read at the end of Phase 3.

2.1.3 The normalized slopes of Phases 2 and 3 (Sn2, Sn3)

The normalized slopes of Phase 2 (Sn2) and Phase 3 (Sn3) are obtained by dividing the slopes of the second and third phases (S2, S3) by the value of $ETCO_2$.

2.1.4 Sn3/Sn2

The quotient of the Sn3 and Sn2 values.

2.1.5 D2min and D2max

The maximum and minimum of the second derivative, the rate of change of the start and end points of Phase 2 (the lower and upper curves).

2.1.6 The α angle (Q)

The angle enclosed by the slopes of Phases 2 and 3.

2.1.7 The area ratio (AR)

The area ratio in the section between the inflection point and the beginning of Phase 3 is the quotient of the area under the curve and the area of the entire rectangle. It is practically the shape of the transition from Phase 2 to Phase 3.

2.1.8 Squared difference (R2SUM)

The sum of the squares of the differences between the points of the raw, original curve and the fitted one. As previously described, the original capnogram curve contains higher frequency noises, which may have physiological reasons. Therefore, these sums of squares are used to examine the differences in the curves of the patients in each group.

2.1.9 Respiratory rates (RR)

In the absence of flow data, the exact length of respiratory cycles cannot be determined from the time capnogram alone. Thus, the length of the given respiratory cycle can be estimated from the combined length of Phases 2 and 3. Examining the measurements in parallel with the flow measurement, we found that the combined length of Phases 2 and 3 is about 65 percent of the respiratory cycle. Currently, we use this ratio to estimate respiratory length, from which we calculate the actual respiratory rate.

3. THE INPUT DATA AND THE STRUCTURE OF THE NETWORK

The data used for teaching the network were as follows:

- All time-based parameters calculated from mainstream measurements: S2T, S3T, $ETCO_2$, Sn2, Sn3, Sn3/Sn2, D2min, D2max, Q, AR, R2SUM, RR (Separate records for each breathing cycle).
- Gender of the patient.
- Class of the patient's age at the time of examination. (The patient's age was divided into 10-year-long classes. For example: 13 years old, 17 years old -> class: 1, 33 years old -> class: 3, 60 years old, 62 years old -> class: 6, etc. This was necessary because without classification only a few measurements would belong to some ages, which would impair the effectiveness of learning.)
- Class of the patient's body weight at the time of examination. (The patient's body weight was divided into classes of 10 kilograms, in the same way as for age.)

We used one label for teaching, which was a manual medical diagnosis of the patient for the test. (One test could include several measurements. One measurement could only belong to one test. One test could only have one diagnosis.) We only used measurements with a "healthy" or "asthmatic" diagnosis. We omitted from teaching the load measurements and the measurements marked as incorrect.

The method was implemented in Java and relied on the Deeplearning4j library [1]. The training of the neural network and the diagnosis prediction with the trained neural network ran on the following configuration: Intel Core i7 10700K CPU, 32GB DDR4 RAM, 256GB SSD, 2TB HDD, Nvidia GeForce 8500 GT video card.

The neural network had 3 hidden layers, each with 50 neurons. For each hidden layer, the activation function was the TANH function. The activation function of the output layer was the SIGMOID function. We gave 6000 epochs for teaching, but according to the log files, no significant learning took place after the 652nd epoch. The training was performed on a record of 3141 healthy and 16670 asthmatic breathing cycles, which lasted 2169 seconds on the configuration given above.

4. RESULTS

Since the training was done per respiratory cycle (the parameters are also calculated separately for each cycle), the diagnosis prediction with the trained neural network is also done per respiratory cycle. For each measurement, we calculated how many cycles of the measurement were "healthy" and how many cycles were "asthmatic". (The prediction is not performed for cycles marked as incorrect.) If the number of healthy predictions is lower than the number of asthmatic predictions, then the entire measurement is considered asthmatic. Otherwise, the entire measurement is considered healthy. The number of measurements used in the prediction was 648. Considering the "asthmatic" diagnosis as positive and the "healthy" diagnosis as negative we found the followings:

- True positive (TP): 517 (79.78%)
- True negative (TN): 107 (16.51%)
- False positive (FP): 23 (3.55%)
- False negative (FN): 1 (0.15%)

TP: The number of measurements for which the manual diagnosis of the test is "asthmatic" and the diagnosis obtained with the neural network is also "asthmatic". TN:

The number of measurements for which the manual diagnosis of the test is ”healthy” and the diagnosis obtained with the neural network is also ”healthy”. FP: The number of measurements for which the manual diagnosis of the test is ”healthy”, but the diagnosis obtained with the neural network is ”asthmatic”. FN: The number of measurements for which the manual diagnosis of the test is ”asthmatic”, but the diagnosis obtained with the neural network is ”healthy”.

The metrics calculated from these are:

- Accuracy: 0.96,
- Precision: 0.96,
- Recall: 1.00,
- F1 Score: 0.98.

Here we used the usual metrics of classifiers, based on the following formulas [5]: Accuracy: (TP + TN) / (TP + FP + TN + FN) Precision: TP / (TP + FP) Recall: TP / (TP + FN) F1 score: 2* precision * recall / (precision + recall)

All of the above metrics must fall within the interval [0.0, 1.0]. The closer the value is to 1.0, the better the result. The total running time of the diagnosis prediction was 240 seconds for 1361 measurements, so the prediction takes an average of 0.1763 seconds per measurement. Comments:

1. The evaluation is somewhat distorted by the fact that we have fewer healthy subjects than asthmatics.

2. It is similarly distorted by the fact that we used all the measurements of all asthmatic and healthy tests from the database for teaching. This is due to the limited number of measurements. In the case of several measurements, we could use only a small part of the measurements during teaching, and test the neural network on the larger part. That way we would get more objective test results.

5. CONCLUSIONS

In this research we developed a neural network based application that uses capnography measurements to help the diagnosis of asthma. Possible future works are the followings:

1. Training the neural network with the raw measurement data as well, not only with the calculated parameters. This is expected to require more hardware resources and time. An advantage may be that the neural network can also learn useful information that is lost during the parameter calculation.
2. Training the neural network with the volumetric parameters or together with volumetric and time-based parameters. The disadvantage here may be that there are no volumetric parameters for purely time-based measurements without flow data.
3. Teaching the neural network for the different severities of asthma, and using the trained neural network to distinguish between them.
4. Teaching the neural network for other diseases, e.g. COPD (and its sub-conditions), ACOS (and its sub-conditions), COVID, etc. Distinguishing these diseases with the help of a trained neural network.

6. ACKNOWLEDGMENTS

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