Computerized Pulmonary Artery Catheter Waveform Interpretation

Jaime Chang
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Abstract

The pulmonary artery catheter (PAC) has been used for decades in the diagnosis and treatment of critically ill patients, but knowledge of PAC waveform interpretation remains inadequate among physicians and nurses. Inspired by the relative success of EKG interpretation programs, this study investigates the feasibility of computerized PAC waveform interpretation. Clinician-provided contextual data, accompanying EKG data, and manually pre-processed waveform data were provided as input, and the ability of classifiers to recognize dangerous situations, system problems, waveform locations, and underlying patient physiology was evaluated. The dataset consisted of 66 waveforms classified by experts, and the classifiers tested were simple logistic regression, 1-nearest neighbor, decision tree, naïve Bayes, and neural network. Under 4-fold cross-validation, 1-nearest neighbor had the most success at classifying accurately, but the neural network had a high area under the receiver-operator curve more consistently across the four classification tasks. All classifiers were good at identifying location. The results of this feasibility study are encouraging and suggest that computerized PAC waveform interpretation may be useful to clinicians.

Introduction

Introduced into the intensive care unit (ICU) over thirty years ago, the PAC is used in the diagnosis of cardiopulmonary disturbances and for assessing and monitoring hemodynamic variables in the critically ill. Data derived from pulmonary artery catheterization alter therapeutic decisions in about half of all insertions.[1 2] More than 45 million catheters have been used since 1970.[3] Use of the PAC is considered routine in most critical care areas, and estimated sales of these catheters are between 1 and 2 million annually in the United States.[4]

Recently, however, the presumed beneficial effect of care directed by the PAC has been called into question by both retrospective reviews and prospective, randomized trials. Connors et al. found that PAC use was associated with increased mortality and increased utilization of resources, and subgroup analyses did not reveal any patient group or investigation site for which PAC use was associated with improved outcomes.[5] In the "Canadian" study, Sandham et al. compared PAC-directed therapy with standard care without the use of the PAC and found no benefit to PAC-directed therapy.[6] In the "French" study, Richard et al. randomly assigned patients with acute respiratory distress syndrome (ARDS) or sepsis to management guided by either the PAC or the central venous catheter (CVC) and found no benefit for the PAC group.[7]

One possible reason why the PAC has not yet been shown to be beneficial is that knowledge of how to interpret PAC data is inadequate among physicians and critical care nurses. Iberti et al. administered a 31-question multiple-choice examination to 496 physicians practicing in 13 medical facilities in the United States and Canada to assess their knowledge and understanding of the use of the PAC and interpretation of data derived from it.[8] The mean test score was 67% correct. Gnaegi et al., evaluating 535 French, Swiss, and Belgian physicians in 86 ICUs using the same 31-question examination, discovered similar results.[9] Of note, approximately 50% of the respondents did not correctly identify pulmonary artery occlusion pressure (PAOP) from a clear tracing. Of the 1095 members of the Society of Critical Care Medicine in the United States who responded to a survey assessing attitudes towards and knowledge of PAC use, one-third of the respondents did not correctly identify PAOP on a clear tracing.[10] The evaluation of 168 critical care nurses in southern California by Burns et al. revealed that 39% of the respondents were unable to identify PAOP from a tracing.[4]

This paper investigates the feasibility of accurate computerized PAC waveform interpretation. Computer-assisted interpretation of the superficially similar electrocardiogram (EKG) has a long history[11] and is at least as good as EKG interpretation by a trained research physician.[12] However, the use of computers in interpreting PAC waveforms is still a research topic. deBoisblanc et al., for instance, recently published an article on estimating pulmonary artery occlusion pressure (PAOP) in nineteen closed-chest dogs by an artificial neural network, using pulmonary artery pressure, its first time derivative, and beat duration as neural inputs.[13]

PAC waveforms are more difficult to interpret than EKGs because PAC waveforms are context-dependent. Although clinical information can be informative, EKG waveforms can generally be interpreted in isolation. On the other hand, PAC waveforms are difficult to interpret meaningfully without at least some basic information on the state of the catheter system and the state of the patient (Table 1).

Table 1 – Contextual Information Essential in Analysis of PAC Waveforms

Contextual Information	**Example of Influence on PAC Waveform Interpretation**
Catheter Port	A normal waveform from the proximal port is central venous pressure (CVP). A normal waveform from the distal port is pulmonary artery pressure (PA) or pulmonary artery occlusion pressure (PAOP).
Balloon Status	When properly inflated, the balloon changes the distal port waveform from PA to PAOP.
Accompanying EKG	An accompanying EKG gives the rhythm status and location of P waves, QRS complexes, and T waves in relationship to the PAC waveform. These pieces of information are essential in differentiating *a* and *v* waves on the PAC trace and in the diagnosis of cannon *a* waves.
Respiratory Status	Spontaneous inspiration decreases intrathoracic pressure and the measured PAC pressure. Positive pressure ventilation increases intrathoracic pressure and the measured PAC pressure.
Ventilator Settings	Different settings, such as pressure support and intermittent mandatory ventilations (IMV), modify the interpretation in vastly different ways. If positive-end expiratory pressure (PEEP) is high enough, PAC pressure measurements have to be adjusted accordingly.

Sedation	An awake or lightly sedated patient can take spontaneous negative-pressure inspiratory breaths. A deeply sedated patient can only take ventilator-driven positive-pressure inspiratory breaths.
Transducer Level	The transducer should be at the level of the vascular structure of interest. If the transducer is too high or too low, the measured pressure in the vascular structure would be proportionally too low or too high, respectively.

The PAC waveform itself contains a lot of information that can be processed into various elements. Some simple elements can easily be obtained manually from printouts of PAC waveforms and their accompanying EKGs (Table 2).

Table 2 – Manually Obtainable PAC Waveform Elements

Waveform Element	**Description**
Highest Peak (HP)	For each interval between R waves on the accompanying EKG, the peak on the PAC waveform is the highest pressure in that interval. The highest peak (HP) is the maximum peak across all analyzed intervals.
Lowest Trough (LT)	The lowest trough (LT) is the minimum trough across all analyzed intervals.
HP-LT Difference	This is the difference between HP and LT.
HP-LT Midpoint	This is the midpoint between HP and LT.
Peak Location	This is the location of the peak in relation to R and T waves on the accompanying EKG.
Peak Variation	This is the difference between the maximum peak and the minimum peak across all analyzed intervals.
Trough Variation	This is the difference between the maximum trough and the minimum trough across all analyzed intervals.

Interpretation of PAC waveforms consists of identifying the waveform, recognizing problems and artifacts, and measuring pressures of interest. Measuring pressures is only meaningful after identifying the waveform and confirming that no artifacts or other problems exist, so the first task is classification (Table 3).

Table 3 – Useful Classification of PAC Waveforms

Classification Task	**Description**
Dangerous vs. Safe	A PAC waveform indicating a dangerous situation requires immediate attention.
Problem vs. Non-problem	A PAC waveform that indicates a problem means that there is either a dangerous situation or a problem with the catheter system that is causing an artifact in the waveform.
Location	Identifying the location of the source of the waveform is essential for measuring pressure.
Dominant Feature(s)	Identifying unusual features give clues to the underlying physiology of the patient or the state of the catheter system.

Methods

The data consists of 66 PAC waveforms with accompanying EKGs and other essential contextual information (as described in Table 1). They were classified by a consensus of a critical care attending physician and a critical care nursing supervisor along the four axes of danger, problem, location, and dominant feature(s) (as described in Table 2). The waveform elements described on Table 2 were obtained manually for each waveform. The compiled data, in Microsoft Excel format, is available upon request. An overview of the kinds of waveforms in the dataset is given in Table 4.

Table 4 – Overview of PAC Waveform Dataset

- **Danger:** 5 dangerous, 61 safe
- **Problem:** 14 problems, 52 non-problems
- **Location:**
  - 18 central venous pressure (CVP)
  - 3 right ventricle (RV)
  - 21 pulmonary artery (PA)
  - 22 pulmonary artery occlusion pressure (PAOP)
  - 2 Overwedge
- **Dominant Feature(s):**
  - 15 normal
  - 9 arrhythmias
  - 13 large waves
  - 14 respiratory variation
  - 11 frequency response artifacts
  - 1 improperly leveled transducer
  - 1 unspecified system artifact
  - 2 overwedge

The machine learning software used for classification is the Java data mining program Weka, version 3.4.6.[14] Attribute selection was done using Ranker, which evaluates the worth of an attribute by measuring the information gain with respect to the class and then ranks the attributes accordingly. The entire dataset was used for ranking. The attributes with that were uninformative were discarded (Table 5).

Table 5 – Attribute Rankings

Danger	Problem	Location	Predominant Feature
0.15 peak_high	0.42 pressure_diff	0.90 midpoint	0.69 trough_var
0.12 pressure_diff	0.42 peak_high	0.87 balloon	0.65 peak_var
0.12 trough_low	0.35 midpoint	0.85 peak_high	0.65 peak_location
0.12 midpoint	0.11 peak_var	0.74 port	0.62 peak_high
0.03 port	0.10 port	0.58 pressure_diff	0.61 midpoint
0.03 peak_location	0.10 peak_location	0.57 trough_low	0.57 heart_rate
0.02 heart_rate	0.05 balloon	0.47 peak_location	0.49 ventilation
0.01 ventilation	0.05 heart_rate	0.03 ventilation	0.33 sedation
0.01 sedation	0.04 ventilation	0.02 heart_rate	0.23 balloon
0.00 balloon	0.02 sedation	0.01 sedation	0.08 port
0 peak_var	0 trough_var	0 trough_var	0 pressure_diff
0 trough_var	0 trough_low	0 peak_var	0 trough_low

The Weka classifiers that were investigated include ZeroR (classifying everything as the most common class regardless of attributes), Simple Logistic, IB1 (1-nearest neighbor), J48 (decision tree), logistic regression, naïve Bayes, and Multilayer Perceptron (neural network).

Because of the small dataset, with some classes having very few numbers, 1-nearest neighbor was used instead of K-nearest neighbors (with K greater than 1). The decision tree was built with minimum leaf node of 1. The neural network was built with 5 hidden layers, which is half of the total number of informative attributes. (All other parameters were the defaults for these classifiers in Weka 3.4.6.)

Cross-validation was used to evaluate the success of each classifier. Because the dataset is small, increasing the number of folds would increase the size of the training sets. However, using too many folds would leave the test sets too small. To balance increasing the size of the training sets and keeping the size of the test sets acceptable, four folds were used, so that training sets each contained 49 waveforms and test sets each contained 17 waveforms.

Experiments

Tables 6-9 display the results from running the various classifiers for each type of classification. The kappa coefficient measures pair-wise agreement after correcting for expected chance agreement.[15] When there is no agreement other than that which would be expected by chance, kappa is zero. When there is total agreement, kappa is one. AUC is the area under the receiver-operator curve (ROC).

Table 6 – Dangerous vs. Safe

Classifier	Right %	Wrong %	Kappa	AUC	Significance vs. ZeroR (5% level)
ZeroR	92.4	7.6	0	0.42	
Simplistic Logistic	92.4	7.6	0	0.58	
IB1	96.9	3.1	0.73	0.80	Yes
J48	92.4	7.6	0.58	0.87	
Naïve Bayes	89.4	10.6	0.31	0.89	
Multilayer Perceptron	95.5	4.5	0.55	0.92	

Table 7 – Problem vs. Non-problem

Classifier	Right %	Wrong %	Kappa	AUC	Significance vs. ZeroR (5% level)
ZeroR	78.8	21.2	0	0.46	
Simplistic Logistic	89.4	10.6	0.67	0.96	Yes
IB1	90.9	9.1	0.71	0.84	Yes
J48	86.4	13.6	0.58	0.83	
Naïve Bayes	89.4	10.6	0.69	0.97	Yes
Multilayer Perceptron	89.4	10.6	0.67	0.90	Yes

Table 8 – Location: CVP vs. RV vs. PA vs. PAOP vs. Overwedge

Classifier	Right %	Wrong %	Kappa	AUC (PAOP)	Significance vs. ZeroR (5% level)
ZeroR	31.8	68.2	-0.02	0.46	
Simplistic Logistic	92.4	7.6	0.89	0.99	Yes
IB1	93.9	6.1	0.91	0.98	Yes
J48	93.9	6.1	0.91	0.98	Yes
Naïve Bayes	80.3	19.7	0.72	0.94	Yes
Multilayer Perceptron	89.4	10.6	0.85	0.99	Yes

Table 9 – Predominant Feature

Classifier	Right %	Wrong %	Kappa	AUC (Normal)	Significance vs. ZeroR (5% level)
ZeroR	22.7	77.3	0	0.47	
Simplistic Logistic	54.5	45.5	0.48	0.85	Yes
IB1	45.5	54.5	0.39	0.74	Yes
J48	53.0	47.0	0.46	0.80	Yes
Naïve Bayes	42.4	57.6	0.36	0.84	Yes
Multilayer Perceptron	51.5	48.5	0.44	0.84	Yes

Results

1-nearest neighbor (IB1) was significantly more accurate (at the 5% level) than ZeroR for all types of classifications, while multilayer perceptron provided consistently good ROC results. All classifiers were good at identifying location.

Discussion

This was a study on the feasibility of computerized interpretation of PAC waveforms, and the results are encouraging. However, it is important to note that this study only demonstrates one part of the total task of waveform interpretation. The first part consists of data acquisition and is a challenge in itself.

Three types of data need to be acquired in order to perform the waveform analysis. The first type consists of contextual information that should be easily provided by the clinician: the source port, the balloon status, the patient's respiratory status and level of sedation, and ventilator settings (as applicable). There is no reason why the clinician would not have this information.

When the context is fairly stable, it need not be re-entered for every interpretation. For example, when not actively being used, the pulmonary artery catheter tip (distal port) is left in the pulmonary artery with the balloon down. The proximal port is in the right atrium (or central vein). If the patient's respiratory status, level of sedation, and ventilator settings are also stable, then the PAC waveform interpreter can use these stable context attributes to monitor proximal and distal port waveforms and set off an alarm if it detects any dangerous situations.

The second type of necessary data is an interpretation of the accompanying EKG, but good EKG interpreters already exist.

The third type of necessary data is the result of pre-processing of the PAC waveform itself into higher level elements. In this study, we pre-processed the waveform into elements that could be easily and unambiguously obtained manually. We did this because developing a more sophisticated waveform processor was beyond the scope of this project.

However, more complex elements of the PAC waveform could serve as better attributes. For example, we could calculate such things as the mean pressure, the means of the peaks and the troughs from heartbeat to heartbeat, the standard deviations of the mean/peak/trough, the first time derivative, the second time derivative, and the Fourier transform. We could also standardize the dimensions of a PAC waveform segment between heartbeats and try to match its shape to the shapes of classified segments. This latter task of pattern matching would be analogous to handwriting recognition.

In any case, any automated waveform pre-processor would be useful, even if it were restricted to the primitive elements defined in this study. Manual waveform pre-processing was the most time-consuming part of the data acquisition for this study. Automated waveform pre-processing of a large number of different types of waveforms and patient situations, along with the corresponding context and expert classification would result in a larger training set that would improve the accuracy of computerized PAC waveform interpretation.

As studies have shown, physicians and nurses have difficulty recognizing a PAOP waveform even on a clear tracing.[4 8 9] Computer assistance need not be perfect to still be useful in improving PAC waveform interpretation.

Finally, waveform recognition is only the beginning of PAC waveform interpretation. The rest consists of pressure measurement, and it is non-trivial to teach a computer from which portion of a waveform to measure the desired pressure, even when the computer recognizes what the waveform is.

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