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Game Theoretic Approach for Systematic Feature Selection; Application in False Alarm Detection in Intensive Care Units

Fatemeh Afghah [1], Abolfazl Razi [1], Reza Soroushmehr [2], Hamid Ghanbari [2], and Kayvan Najarian [2]*

[1] School of Informatics, Computing and Cyber Systems, Northern Arizona University, Flagstaff, AZ 86011; {fatemeh.afghah,abolfazl.razi}@nau.edu
[2] Department of Emergency Medicine, University of Michigan, Ann Arbor MI 48109; {ssoroush,ghhamid,kayvan}@med.umich.edu
* Correspondence: Fatemeh Afghah is the corresponsing author for this article. Address: #114, SICCS Building, 1295 S. Knoles Drive, Flagstaff AZ 86011, Phone: +1-928-523-5095, Email: fatemeh.afghah@nau.edu.

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Abstract: False alarm is one of the main concerns in Intensive Care Units (ICUs) and can result in care disruption, sleep deprivation, and insensitivity of caregivers to alarms. Most current methods attempt to suppress the false alarm rate through improving the quality of physiological signals by filtering, and developing more accurate sensors. However, the significant intrinsic correlation among the extracted features from different sensors has been mostly overlooked. A majority of current data mining techniques fail to capture such correlation among the collected signals from different sensors that limits their alarm recognition capabilities. Here, we propose a novel information-theoretic predictive modeling technique based on the idea of coalition game theory to enhance the accuracy of false alarm detection in ICUs by accounting for the synergistic power of signal attributes in the feature selection stage. This approach brings together techniques from information theory and game theory to account for inter-features mutual information in determining salient predictors with respect to false alarm by calculating Banzhaf power of each feature. The numerical results show the performance of this method in enhancing classification accuracy as well as improvement in area under ROC curve compared to other feature selection techniques.

Keywords: False alarm reduction, intensive care units, feature selection, coalition game theory, Banzhaf power.

1. Introduction

As there is no single sensor/device capable of complying with all clinical requirements, multiple therapeutic and monitoring devices are often utilized in the Intensive Care Units (ICUs) to collect real–time data for diagnosis, prognosis, treatment and more generally, patients monitoring. These devices generate visual and acoustic alarms to inform nurses and physicians about changes in patient's condition or a failure in device functionality [1]. However, the rate of false alarm generation is too high, which can result in disrupting the monitoring procedure in severe situations, alarm fatigue and desensitization of clinical staff to the alarms and hence ignoring or delayed reaction to true alarms [2,3]. As reported in [4,5], caregivers are usually overwhelmed with 350 alarm conditions per patient per day, of which 80-99% are meaningless or false [6–8]. Therefore, false alarms are widely considered the number one hazard imposed by the use of medical technologies. The Emergency Care Research

Institute (ECRI) named alarm hazards as number 1 of the "Top 10 Health Technology Hazards" for 2012, 2013 and 2015 [9–11].

False alarm might happen due to low quality of signals [2] as a result of several factors such as noise, motion artifacts, missing data, and technical defects. Various methods have been proposed to reduce false alarms [1,12–18], which can be generally classified to learning and non–learning methods. In the learning category, a labeled dataset is usually available and a set of features is extracted from the dataset to train a model using a portion of the dataset. Then, this model is tested and validated using a validation technique. Imhoff et al. [1] have reviewed a number of learning and statistical approaches and discussed their potential use for clinical applications, particularly, false alarm reduction. Behar et al. [17] have designed an support vector machine (SVM)-based method to estimate the quality of an electrocardiogram (ECG) segment using signal quality indecies (SQIs). SQIs are used to assess the quality of a signal or its level of noise. This model could reduce the number of false alarms as it can eliminate low quality ECG segments with high accuracy. Gambarotta et al. [2] have reviewed the techniques on quality scoring of ECG and arterial blood pressure (ABP) signals and also surveyed the algorithms that exploit the relationship among ECG, ABP and photoplethysmogram (PPG) to reduce the false alarm rate. Among the learning methods proposed in the literature, they referred to SVM, naive Bayes, multilayer perceptron (MLP) and linear discriminant analysis (LDA). Ansari et al. [16] performed band-pass filtering on ECG and pulsatile signals and also trend estimation on ECG signals. They applied different QRS-complex detection methods and classified beats using a decision tree approach. Finally they developed another decision tree classifier to classify true and false alarms. Antink et al. [13] applied band-pass filtering, peak detection, fast Fourier transform (FFT), principle component analysis (PCA), and some statistical analyses and extracted a number of features to train machine learning methods. They applied four classifiers: random forest, SVM binary classification decision tree and regularized linear discriminant analysis for classifying alarms. Zhang and Szolovits used ECG, plethysmography, blood pressure, arterial and venous oxygen saturation, and oxygen perfusion and trained a classification tree and also artificial neural networks to classify the alarms. They showed that training with 8 hours of the data can result in better performance compared with standard thresholding methods [19]. Li and Clifford [18] extracted 147 features and SQI metrics from ECG, ABP, PPG and SpO2 and trained a random forest classifier. They used 10–fold cross validation technique and achieved the sensitivity of 100% and specificity of 24.5%. Salas-Boni et al. [20] used ECG signal and applied wavelet transform to extract the features. They developed an L1-regularized logistic regression classifier and achieved a false alarm suppression of 25.5% with zero true alarm suppression.

Among the non–learning methods, we can refer to the method proposed in [21]. In this method, a wavelet transform is applied to the ECG signal to remove its noise. Then, the quality of vital signals (ECG and ABP) in intensive care patients is measured using SQIs. After that the combination of SQI, Heart Rate Variability (HRV) and ABP is used for the judgment of false alarms. Delayed activation of alarms is another simple approach to decrease the false alarms [6,22,23]. Scmid et al. [22] and Teo et al. [24] used ECG, ABP and PLETH signals and designed a majority voting approach with a fixed threshold to determine if an alarm is true or not. Aboukhalil et al. [15] used a database of MIMIC II to analyze five types of ECG arrhythmia. They developed an algorithm based on the morphological and timing information of ABP signal and achieved the false alarm suppression rate of up to 42.7%. Li and Clifford [25] proposed an SQI to assess the quality of ABP signal and reject the noisy ones. They estimated the ABP-derived HR and compared it with the monitor's HR threshold and rejected the false HR-related arrhythmia. They could reduce the false alarm rates of extreme bradycardia and extreme tachycardia to 74.13% and 53.81%, respectively.

One of the challenges facing the above mentioned methods is that in the feature extraction phase they might exclude the features that individually have low impact on the model performance while by their combination with other features they can improve the performance. These methods consider either the effect of individual features on the target or the inter–feature mutual information to obtain higher performance. Therefore, they might discard the features that are relevant to the target class but are highly correlated to the already selected features .

To suppress the false alarm in ICUs, here we develop a new coalition game–theoretical model based on *Banzhaf power* index that accounts for interdependency among the extracted features and their relevancy to the target class. Coalition game theory has been recently utilized in data analysis problems to improve the performance of feature selection, where features are modeled as game players [26–28]. In majority of these existing game-theoretical approaches, the importance of features on classification accuracy is measured by *Shapley value*. The shapely value of each feature is defined as its contribution in improving the classification accuracy considering all possible coalitions of the features with any arbitrary size. While this method can have a considerable impact on capturing the higher-level correlation among features (e.g more than mutual correlation between two features), it involves a high computational complexity to calculate this factor for all possible grouping of the features, in particular in the presence of a large number of features. In [27], we utilized a Shapley value-based game theoretic feature selection method to determine the salient features over a heterogeneous data set to predict the hemorrhage severity, where we computed the importance of each feature using multi-perturbation Shapely value over all possible coalitions of size $4-10$ due to intractable computational complexity of calculating Shapley value over larger coalitions.

In [29], we studied the problem of false alarm reduction in ICUs, where three main signals; ECG, ABP, and PLETH were used as the inputs. In the first stage, wavelet coefficients of each signal at different levels of decomposition were calculated. Then, a number of statistical and information theory-based features resulting from wavelet coefficients were extracted for each level. A Shapley value-based feature selection approach was utilized to reduce the possibility of removing high-impact features that are highly correlated with other selected ones. While the Shapley value was only calculated for small size coalitions, the feature selection method still involved a considerable computational complexity. More importantly, considering smaller coalitions of features resulted in reducing the accuracy of the alarm detection model. To address these challenges, in this paper, we propose a new game-theoretic feature selection method based on utilizing *Banzhaf power* to declare salient features with comparable accuracy but much less complexity. This metric which is proportional to the number of times that a feature is a critical player for a coalition. In the proposed model, we define an information-theoretic notion for Banzhaf power, where a feature is determined to have a critical impact on a set of features if it increases the relevancy of the selected feature set on a target class and also is interdependent on more than half of the members in the set. The numerical results validates the desirable performance improvement of this method in reducing the false alarm rate compared to existing feature selection techniques.

The rest of this paper is organized as follows. List of the abbreviations used in this paper is presented in Section 4. In Section 2, an introduction to the data set studied in this work is provided. Section 3 introduces the proposed signal analysis and feature extraction techniques. The proposed coalition-based game theoretic feature selection method based on Banzhaf power is presented in Section 4. The numerical analysis results are presented in Section 5, followed by conclusion in Section 6.

2. Description of Data Source

In this work, we use the publicly available Physionet Challenge 2015 database [30,31]. The database used for this study was produced by four hospitals in the USA and Europe, using monitors with different manufacturers, unit-specific protocols, software versions and unit types. The definition of the alarms is presented in Table 1 [30]. Measurement for three vital signals of ECG, PLETH, and APB are utilized where each alarm is labeled as *true*, *false*. Each alarm was reviewed by a team of experts at least two of whom agreed that the alarm was either true or false. These alarms are assumed to be at least 5 minutes apart and are triggered 5 minutes from the beginning of each record while the onset of the events is within 10 seconds of the alarm (i.e. between 4:50 and 5:00 of the record). The resolution

Table 1. Alarms definition

Alarm Type	Definition
Asystole	No heartbeats for at least 4s
Extreme Bradycardia	Heart rate less than 40bpm for 5 consecutive beats
Extreme Tachycardia	Heart rate higher than 140bpm for 17 consecutive beats
Ventricular Tachycardia	At least 5 ventricular beats with heart rate higher than 100bpm
Ventricular Flutter/Fibrillation	Fibrillatory, flutter, or oscillatory waveform for at least 4s

and frequency of each signal are 12bit and 250 Hz, respectively. Also, each signal has been filtered by an finite impulse response (FIR) band pass [0.05 to 40Hz] and mains notch filters. The signals might suffer from movement artifact, sensor disconnects, interference from pacemakers and other events.

3. Signal Analysis and Feature Extraction

Extracting relevant features from the entire time-series signals is a key step in detecting the false alarms, as considering the original signals results in a large number of highly correlated features compared to the sample size that increases the chance of over–fitting the model to the training data. Here, we apply discrete wavelet transforms (DWT) on the 1–D input signals, ECG, PLETH and ABP. This method is utilized due to its ability to separate details in signals comparing to other transforms and to eliminate the noise with a low distortion rate. The DWT's capability to detect specific time-frequency component of ECG signals has motivated several researchers to utilize this method in several related applications [32–34].

A set of wavelets defines a filter bank which can be used for signal component analysis and the resulting wavelet transform coefficients can be further applied as signal features for classification [35]. DWT components are shifted and scaled versions of the mother wavelet defined as:

$$\psi_{i,j}(t) = 1/\sqrt{2^i}\psi(\frac{t - j \times 2^i}{2^i}) \tag{1}$$

where i, j are scale and shift parameters, respectively and ψ for a Daubechies wavelet of class D-2N is defined as:

$$\psi(t) = \sqrt{2}\sum_k (-1)^k h_{2N-1-k} \times \phi(2t-1), \tag{2}$$

$$\phi(t) = \sqrt{2}\sum_k h_k \times \phi(2t-k)$$

where, h shows a high pass filter. At each level of decomposition process, DWT decomposes the signals into approximate and detail coefficients. Approximation set is obtained by applying a high–pass filter at low scales and detail coefficients are computed by applying a low–pass filter at high scales. We used Daubechies 8 (db8) for ECG signal as there is a good match between the shape of ECG signal and this wavelet. Daubechies 4 is used for PLETH and ABP signals for the same reason.

Wavelet coefficients are calculated by convolving the high pass filter, h and the corresponding low pass filter, $g_k = h_{2N-1-k}$, with a signal and then the results are down–sampled. The calculated coefficients are shown as $X = [E_1, ..., E_l, A_1, ..., A_l, P_1, ..., P_l]$, where l shows the number of decomposition levels, (here $l = 6$). E_i, A_i and P_i, respectively show the wavelet coefficients of ECG, ABP and PLETH signals. For $i = l$, each of these parameters shows the detail coefficients and for $i \neq l$ each of them shows the approximate coefficient. Approximate and detail coefficients can be respectively calculated from (3) and (4)

$$a_i(t) = \sum_k a_{i-1}(t)h_{2t-k} \tag{3}$$

$$d_i(t) = \sum_k a_{i-1}(t) g_{2t-k} \tag{4}$$

where a_{-1} shows the input signal (i.e. ECG, ABP or PLETH).

Each of the three aforementioned signals are decomposed into 6 levels by convolving the high-pass and low–pass filters. Feeding all wavelet coefficients as features into the classification algorithm is not efficient and may significantly decrease the generalization property of the trained model due to over–fitting. Therefore, we reduce the number of features by extracting representative statistical and information–theoretic properties of the wavelet vectors as summarized in Table 2. In calculating information–theoretic properties (e.g. Entropy), we first discretized the coefficients using quantization levels obtained from Lloyd's algorithm [36] and then use the empirical distribution as an estimate for the unknown probability distribution from which the coefficients are derived.

Table 2. Statistical and Information-theoretic features of wavelet vectors.

No	Feature	No	Feature	No	Feature
1	mean	8	std (σ)	15	Interquartile
2	mode	9	μ_3		Range
3	median	10	μ_4	16	Shannon Ent.
4	max	11	coef. of var	17	Log Ent.
5	min	12	kurtosis	18	$n_T(max\{X_i\}/2)$
6	range	13	skewness	19	$n_T(\sqrt{\sum X_i^2})$
7	variance	14	H mean	20	$n_T(5\sqrt{\sum X_i^2})$

In Table 2, features 1 to 10 are typical statical properties of the signal, where μ_n is the n^{th} standardized sample moment, $\mu_n = \frac{\sum_{i=1}^{N}(X_i - \bar{X})^n}{N}$, in which $\bar{X} = \frac{\sum_{i=1}^{N} X_i}{N}$, and $X_1, \ldots, X_N$ are the N^{th} wavelet coefficients associated with each signal probe. *Kurtosis* measures the peakedness of distribution and is defined as the ratio of the forth standardized moment to the square of variance, $\kappa(X) = \frac{\mu_4(X)}{\sigma_4(X)}$. *Skewness* is a measure of the symmetry of distribution around zero and is defined as $\lambda(X) = \frac{\mu^3(X)}{\sigma^3(X)}$. *Harmonic mean* (H mean) is defined as $\frac{N}{\sum_{i=1}^{N} 1/X_i}$. *Interquartile range* is calculated based on the difference between the 75^{th} and 25^{th} percentiles. *Shannon entropy* is an information theoretic property of the square of coefficients approximated by their sample counterparts and calculated as $H(X^2) = -\sum_{i=1}^{N} X_i^2 \log_2 X_i^2$ and *Log energy* is defined as $\sum_i \log X_i^2$. Finally, $n_{T(\alpha)}$ counts the number of times that the value of wavelet coefficients exceed the threshold α.

$$n_T(\alpha) = \sum_{i=1}^{N} \mathbf{1}(|X_i| > \alpha) \tag{5}$$

where, $\mathbf{1}(.)$ shows the indicator function. These features collectively capture the properties of the signal at different decomposition levels and are used as input for the proposed feature selection method.

4. Proposed Coalition Game-theoretic Feature Selection Method

In this section, we provide a brief introduction to coalition game theory, and then describe the proposed feature selection method using Banzhaf power. Unlike non-cooperative games in which players act individually [37–39], *coalition game* or *cooperative game* refers to a class of game theoretical approaches that study the set of joint actions taken by a group of players. Outcome of a coalition game is defined by how players can form coalitions and how the coalition payoff can be divided among its members [40].

A coalition game can be defined with a pair of $(\mathcal{N}, v)$, where $\mathcal{N} = \{F_1, F_2, \ldots, F_n\}$ is the set of players with cardinality of n (i.e. $|\mathcal{N}| = n$). The *characteristic function*, v is a real–valued function defined on the set of all coalitions, $v : 2^{\mathcal{N}} \rightarrow \mathbb{R}$ and represents the total payoff that can be gained by the members of this coalition. We use transferable utility coalition (TU–coalition) game for which the characteristic function satisfies the following conditions:

1. characteristic function of an empty coalition ϕ is zero ($v(\phi) = 0$);
2. for two disjoint coalitions $\mathcal{S}_i$ and $\mathcal{S}_j$, ($\mathcal{S}_i, \mathcal{S}_j \subseteq \mathcal{N}$), the characteristic function of their union has super–additivity property, meaning that $v(\mathcal{S}_i \cup \mathcal{S}_j) \geq v(\mathcal{S}_i) + v(\mathcal{S}_j)$.

Different solutions have been defined to measure the role (importance) of a player in a transferable utility coalition game including *Shapley value* [41], *Banzhaf power* [42], and *Banzhaf value* [43]. In our proposed feature selection method, the importance of the features is measured using *Banzhaf power*. To define this metric, we first need to introduce the concept of *simple game*.

A simple game refers to a class of coalition games with characteristic function satisfying the following conditions[44]

1. $v(\mathcal{S}) \in \{0, 1\}$, For all $\mathcal{S} \subset \mathcal{N}$,
2. $v(\phi) = 0$, $v(\mathcal{N}) = 1$, and
3. For $\mathcal{S}, \mathcal{T} \subset \mathcal{N}$, if $\mathcal{S} \subset \mathcal{T}$, then $V(\mathcal{S}) \leq v(\mathcal{T})$ (monotonicity).

Based on the first property, the coalitions are divided into two sets of winning coalition, $W(v) = \{\mathcal{S} \subset \mathcal{N} | \; v(\mathcal{S}) = 1\}$ and losing coalitions defined as $L(v) = \{\mathcal{S} \subset \mathcal{N} | \; v(\mathcal{S}) = 0\}$. In these games, a player F_i is called a *swinger* if the removal of this player from a winning coalition $\mathcal{S}$ converts it to a losing coalition, meaning that $V(\mathcal{S}) = 1$ and $v(\mathcal{S} \backslash \{F_i\}) = 0$.

The Banzhaf power for player F_i, $\beta_i(v)$ represents the fraction of times that player has a critical role in converting a losing coalition to a wining one and is defined as the expectation of player F_i to be a swinger in a simple game model assuming that formation of all coalitions are equally probable as defined below,

$$\beta_i(v) = \frac{\eta_i(v)}{2^{n-1}} \tag{6}$$

where $\eta_i(v)$ counts all coalitions for which the player F_i is a swinger (i.e. $\{\mathcal{S} : \mathcal{S} \subset \mathcal{N} \setminus \{F_i\}, \nu(\mathcal{S} \bigcup \{F_i\}) - \nu(\mathcal{S}) = 1\}$).

In continue we discuss our proposed coalition-based feature selection method, in which the features are considered as the players of the game, and the characteristic function of a coalition, v, is measured by contribution of its members (features) to the performance of the classifier. We measure the contribution of each feature in the game noting all possible coalitions of the players using Banzhaf power. The criterion to determine the most informative subset of features is the relevance of this set to the target class as well as the interdependence among the group members. If the relevance of the feature F_i on target class C, $R(F_i; C)$ is defined by their mutual information, $R(F_i; C) = I(F_i; C)$, the relevance of coalition $\mathcal{S}$ on target class C can be approximated as [45]:

$$R(\mathcal{S}; C) \approxeq \frac{1}{|\mathcal{S}|} \sum_{F_j \in \mathcal{S}} [I(F_j; C)], \tag{7}$$

Likewise, the change of relevance of a coalition $\mathcal{S}$ on target class C due to the knowledge of feature F_i, ($F_i \notin \mathcal{S}$) is approximately

$$I(\mathcal{S}; C|F_i) \approxeq \frac{1}{|\mathcal{S}|} \sum_{F_j \in \mathcal{S}} [I(F_j; C|F_i) - I(F_j; C)], \tag{8}$$

Moreover, two features F_i and F_j are defined to be interdependent of each other if the relevance between F_j and the target class C is increased when F_i ($I(F_j; C|F_i) > I(F_j; C)$), meaning that the impact of this feature cannot be overlooked in the model [46]. Parameter $\gamma^i_{\mathcal{S}}$ is defined to count the number of features in coalition $\mathcal{S}$ that are interdependent on feature F_i as follows

$$\gamma_i^{\mathcal{S}} = \mathbf{1}(I(F_j; C|F_i) > I(F_j; C)), \text{for all } F_j \in \mathcal{S}. \tag{9}$$

where $\mathbf{1}(.)$ is the indicator function.

In order to select the most informative subset of features, we first determine the impact of feature F_i on all possible coalitions of features excluding F_i, $\{\mathcal{S} : \mathcal{S} \subset \mathcal{N}, F_i \notin \mathcal{S}\}$. Feature F_i is a swinger for coalition $\mathcal{S}$, if it increases the relevance of this coalition on the target class and also if it is interdependent with at least half of the members of coalition $\mathcal{S}$. Then, a swinger index ζ_i for feature F_i is defined as:

$$\zeta_i = \begin{cases} 1, & I(S; C|F_i) \geq 0, \gamma_i^{\mathcal{S}} \geq \frac{|S|}{2} \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

Consequently, the Banzhaf power of feature F_i calculates the ratio of all coalitions for which player F_i is a swinger, $\eta_i(v) = \frac{1}{2^{n-1}} \sum\limits_{S \subset N ß} \zeta_i^{\mathcal{S}}$. This parameter quantifies the power of features in turning the loosing coalitions into winning ones and hence can be used to choose the top informative features.

5. Numerical Analysis and Discussion

In this section, we examine the utility of the proposed approach in selecting informative features from three signal sources to verify alarm validity. For this study, we use the Physionet Challenge 2015 database as described in section 2. We first apply six–level wavelet decomposition using Daubechies 8-tap as the pair of father and mother wavelets to signals to obtain time–frequency information at different resolutions. As each sample includes 3 signals, it is represented by 18 vectors of wavelet coefficients using six levels. Subsequently, 20 statistical and information-theoretic features are extracted from each vector, resulting in a total of 360 features. The list of features are provided in table 2.

The proposed coalition game based on Banzhaf power evaluates the average marginal importance of each feature when joining any potential coalition of features. The metric we use is the interdependency of newly added features with the coalition members as defined in section 4. In order to obtain interdependency, we first discretized the wavelet coefficients. The quantization levels are obtained from Lloyd algorithm, which minimizes the MSE error between the continuous values and the quantized versions for a training dataset and a given number of quantization levels (here we choose 5 quantization levels) [36]. The quantized values are used to calculate the required mutual information which further is used to calculate features' interdependencies. Then, a swinger index $\zeta_i^{\mathcal{S}}$ for each feature F_i with respect to coalition $\mathcal{S}$ is set to 1 if the feature is interdependent with at least half of the coalition members (10). The Banzhaf power for each feature F_i is calculated as the ratio of coalitions for which the feature F_i is a swinger. We rank the features based on their Banzhaf powers and choose the top-20 features.

In order to evaluate the relevance of the obtained features, we used *Weka ver. 3.6* package and applied state-of-the-art feature selection methods to the extracted features and selected top-20 of them for each method. In this experiment, the following attribute selection techniques are utilized: i) The Correlation-based Feature Subset Selection (CFS) that selects a subset of features with the highest correlation with the labels and the lowest correlation with each other [47]; ii) The Chi-square method which simply chooses a subset of features by evaluating their chi-squared statistic with respect to the class label [48]; iii) The Gain ratio method, an information-theoretic based method that minimizes the conditional entropy of class given the selected features [49]; iv) The RELIEF method that evaluates the importance of a test feature set by examining the difference of Euclidean distances for randomly selected samples with the nearest samples of the same and different classes using the test feature set [50], v) The SVM-based ranker, in which the features are ranked by the square of their weights assigned by the SVM classifier [51]. For completeness of comparisons, we also employed popular sparsity imposing regression methods including LASSO [52] and logistic regression [53] and selected the top-20 features with highest absolute coefficients in the model. We also included the results for the classification accuracy using all 360 features that is shown by NoFS in Figs. 1 and 2. Finally, the results are also compared with our recently developed Shapely-based coalition game theoretic feature selection method [27,29].

In order to compare the performance of the aforementioned feature selection methods, Bayes-Net with 10-fold cross validation is selected as a representative classifier to classify the alarms into false and true alarms. It is worth mentioning that definition of the proposed feature selection method is independent of the choice of classifier technique and it can be applied to all classification techniques. The classification success rates, and the sensitivity and specificity for all aforementioned feature selection methods are presented in Figs. 1 and 2.

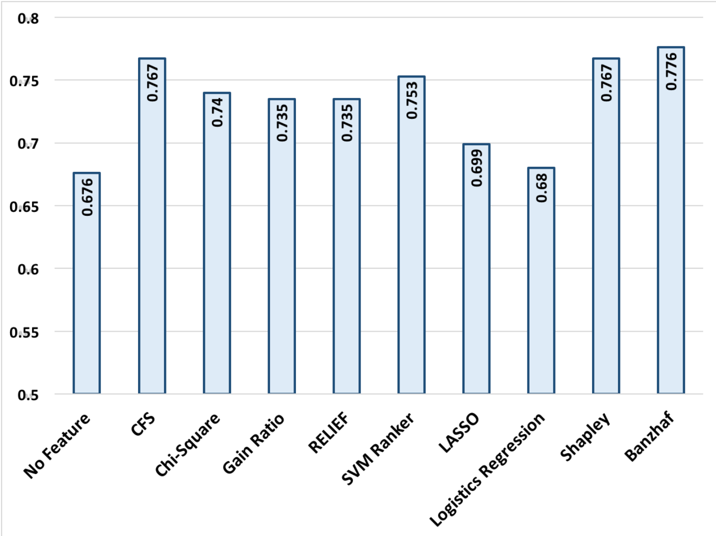

Figure 1. False alarm detection rate for various feature selection methods using top-20 features. Bayes-Net classification with 10-fold cross validation is used to classify alarms into true and false alarms.

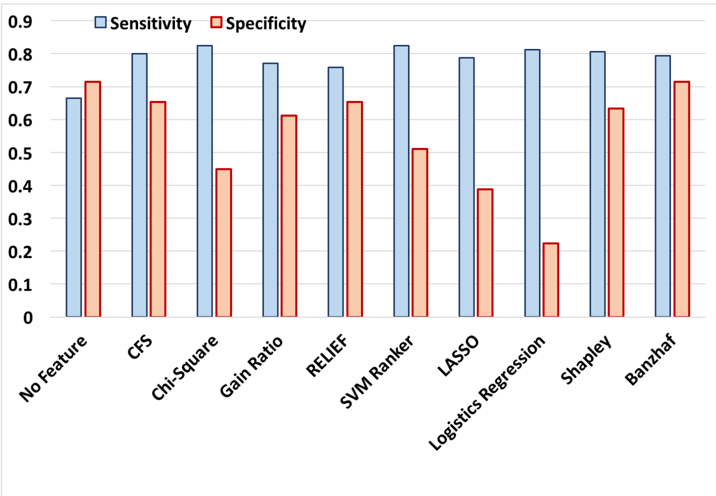

Figure 2. Sensitivity and specificity of various feature selection methods using top-20 features and Bayes-Net classification with 10-fold cross validation.

The results in Fig. 1 represent the alarm classification success rate which is the ratio of successfully classified alarms. Fig. 1, represents the specificity and sensitivity of the classifier using features

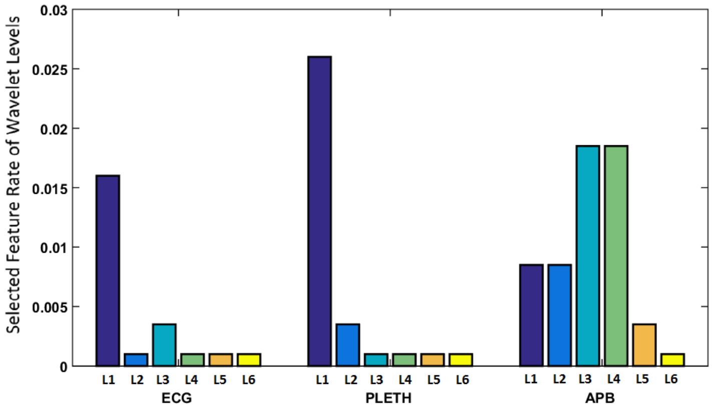

Figure 3. Relative appearance of selected features in different levels of wavelets for the vital signals.

reported by different methods. Sensitivity is calculated as the ratio of recognized true alarms to the number of all true alarms. Likewise, specificity is calculated as the ratio of recognized false alarms to the number of all false alarms. In other words, a higher sensitivity is desired for not missing a true alarm and an acceptable level of specificity is required not to report a false alarm. The trained classifier shows a better sensitivity compared to majority of feature selection methods, which is desired since missing a true alarm may have catastrophic consequences.

The results show that the proposed algorithm outperforms majority of other feature selection methods in recognizing true and false alarms with a low computation complexity. Interestingly, the false alarm recognition rate (specificity) is substantially improved compared to the best competitors methods, while the true alarm recognition (sensitivity) remains almost at the same level. The low success rate for NoFS is somewhat expected and demonstrates the value of feature selection, since incorporating all features in classification not only increases the time and computational load of the classifier, but also decreases the classification accuracy due to the well-known over-fitting problem. It is also observed that the proposed method provides a similar level of accuracy compared to our previously developed coalition-based game theoretical feature selection method using Shapely value. However, the Banzhaf-based coalition game includes much less computational power. In Shapely-based coalition game, the marginal importance of a feature F_i when joining a coalition $\mathcal{S}$ with $|\mathcal{S}|$ members is calculated by checking all $2^{|\mathcal{S}|}$ permutations. However, in Banzhaf-based coalition game, in order to evaluate marginal importance of a feature F_i with respect to coalition $\mathcal{S}$, we examine interdependency of this feature with $|\mathcal{S}|$ members, that requires much less calculations.

Fig. 3 demonstrates the rate of selected features from each of the wavelet levels for all signals. As can be seen, the features in low levels of ECG, corresponding to smoother waves such as P and T have proved to be more significant for this decision making task. A similar observations can be made regarding the low level features of PLETH. However, the medium levels of ABP appear to be selected more frequently in the process. The frequencies of variations in these levels of wavelet decomposition seem to correspond to the informative patterns in dicrotic notch.

Fig. 4 compares the ROC curve for different feature selection methods using Bayes-Net classification with 10-fold cross validation. As shown in Table 3, the proposed game-theoretic feature selection method based on calculating Banzhaf power achieves the highest area under the ROC curve (AUC=0.7432) compared to well-known feature selection techniques.

6. Conclusions

In this paper, a novel coalition game theoretic-based feature selection method is proposed to improve the accuracy of false alarm detection as one of the critical yet unresolved concerns in intensive care units. The proposed method accounts for information–theoretic correlation among the features in

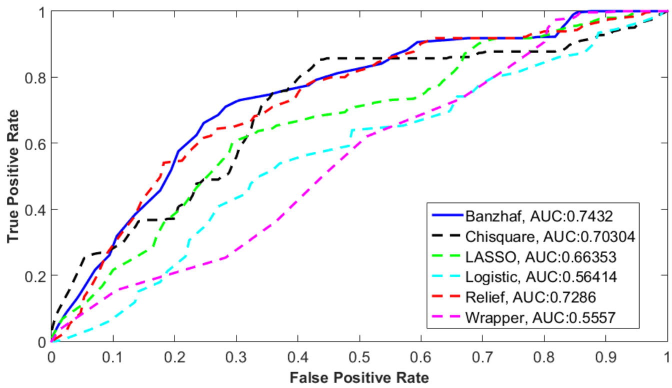

Figure 4. ROC curve for different feature selection methods

Table 3. Comparison of area under ROC curve for different feature selection methods

Feature Selection Method	Area Under ROC Curve (AUC)
Proposed method based on Banzhaf power	**0.7432**
ChiSquare	0.70304
LASSO	0.66353
Logistic	0.56414
Relief	0.7286
Wrapper	0.5557

all possible coalitions of them. This feature selection problem is defined as a *simple* coalition game, where the average contribution of each feature (game player) is determined by Banzhaf power. A feature is defined to plays a critical role in a coalition if increased the relevancy of the coalition on target class and also was interdependent on more than half of the coalition's members. The numerical results presented in this paper were created using Bayes-Net classifier and showed the significant performance of the proposed model in false alarm detection as well as increasing area under the ROC curve compared to other feature selection techniques including Chi–square, Gain Ratio, and Relief methods. It should be noticed that the proposed model can be applied to any commonly used classification methods.

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Abbreviations

The following abbreviations are used in this manuscript:

Table 4. List of abbreviations

Acronym	Abbreviation
ABP	Aeterial Blood Pressure
CFS	Correlation-based Feature Subset Selection
DWT	Discrete Wavelet Transform
ECG	Electrocardiogram
FFT	Fast Fourier Transform
FIR	Finite Impulse Response
ICU	Intensive Care Unit
LDA	Linear Discriminant Analysis
MIMIC	Multiparameter Intelligent Monitoring in Intensive Care
MLP	Multilayer Perceptron
PPG	photoplethysmogram
PCA	Principle Component Analysis
PPI	Protein-Protein Interaction
SQI	Signal Quality Indecies
SVM	Support Vector Machine
TU	Transferable Utility
HRV	Heart Rate Variability

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