New Feature Selection Methods for Qualification of the Patients for Cardiac Pacemaker Implantation

G Ilczuk[1], R Mlynarski[2], W Kargul[2], A Wakulicz-Deja[1]

[1] Institute of Informatics University of Silesia, Sosnowiec, Poland
[2] Electrocardiology Department of Medical University of Silesia, Katowice, Poland

Abstract

Implantation of a cardiac pacemaker is a complicated procedure. The success of the procedure depends directly on the proper classification of patients and the choice of the type of pacing. Machine learning algorithms can support this process. The most important element of these is the feature selection process. In this paper we present the results of our own implementation of feature selection methods, working on the electrocardiological datasets of 4316 patients with severe heart rhythm disorders and qualified for pacemaker implantation. For the research, we chose the two most promising algorithms (CFS and Chi-square). In all cases it was possible to reduce the initial set of attributes by 60%. Due to the reduction of the search space the number of generated decision rules was decreased by factor of 6-10. Because of this, practical cardiological validation of rules is easier and faster, more general rules adapt better for recognition of new cases and computational effort is reduced, which was confirmed in clinical practice.

1. Introduction

Since the implantation of the first cardiac pacemaker in 1958 by doctor Ake Sening and engineer Rune Elmqvist in Stockholm, there has been gigantic progress in this field of medicine, including both the range of the equipment and the techniques of implantation.

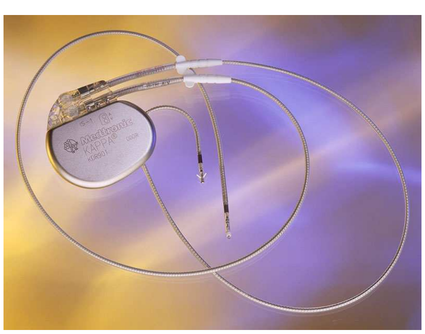

Figure 1. DDDR type pacemaker (photo: Medtronic Inc.)

Today electrotherapy is a rapidly developing field of invasive cardiology [1,2]. The most common types of antiarrhythmic devices are cardiac pacemakers – Fig. 1 shows a DDD type pacemaker. Despite the huge propagation of this method, qualification of patients for implantation still causes many problems. Meanwhile, the success of the procedure depends directly on the proper classification of patients and the choice of the type of pacing. Depending on the disease that is the basis for implantation, we have the possibility of utilizing different types of stimulation (pacing) [3]. The most common types of heart stimulation are presented in the table 1.

Table 1. Basic types of stimulations in permanent pacing.

Type of pacing	Description
AAI	Stimulation of right atrium
VVI	Stimulation of right ventricle
DDD	Stimulation of right atrium and right ventricle
VDD	Stimulation based on sensing from the right atrium and both sensing and pacing of right ventricle

It is possible that an artificial decision system can support the treatment of patients both before and after pacemaker implantation. Therefore in our research we focus on a complete decision support system which contains the following modules:

1. Import subsystem – responsible for importing data from medical information systems into our storage subsystem
2. Preprocessing subsystem – transforms raw data into a form suited for further data processing. Additionally, noise and redundant data are removed based on a statistical analysis
3. Feature selection module – responsible for selecting an optimal set of attributes for a generation of decision rules

4. Rule induction subsystem – uses algorithms based on Rough Sets MLEM2 algorithm for generating decision rules
5. Visualization module – transforms the collected knowledge to a form which is easily understandable and verifiable by humans.

Our earlier experiments showed that the key element in the knowledge extraction process is a proper selection of important features/attributes. Feature selection is an essential data preprocessing step prior to applying a learning algorithm. If the processed information contains irrelevant, unreliable or redundant data then the process of knowledge discovery is more difficult and the achieved results are difficult to analyse. One way to remove the unneeded information is the selection of a subset of attributes from an original dataset for further processing. Our goal is to automatically remove unneeded and redundant attributes without decreasing classification accuracy. It is necessary to remember that although feature selection is very important, it is only one element of a complex system.

1.1. Aim of the study

The aim of the study was to implement and validate several feature selection algorithms as a part of the complex system for the support of diagnosis and treatment of patients with heart rhythm disorders.

2. Methods

In the research were used two different attribute selection algorithms: CFS (Correlation-based Feature Selection) and the Chi-square test. In the preliminary tests these two algorithms showed superior results both for accuracy and speed in comparison to the Wrapper and Quickreduct methods [4,5]. The selected algorithms belong to a filter group of attribute selection methods, which has two main advantages in the field of medicine. Firstly, it uses the general characteristics of data to filter out undesirable features independent of a learning algorithm, which reduces the danger of data over fitting. Secondly, filter algorithms are significantly faster in the analysis of the large datasets typically found in the medical domain.

All presented algorithms were implemented in the Data Exploration system written in Java 6.0. Input data for the selected algorithms was information about 4316 patients hospitalized in the Electrocardiology Department of the Medical University of Silesia in Katowice, Poland. This data was imported from a clinical information system and transformed into classification tables for the data-mining appliance. At the end of the data preparation phase, a set of 13 attributes characterizing the current patients' health status, including symptoms and the results of tests such as: ECG and echocardiography data were created. Information about previous heart diseases and other diseases that can interfere with the cardiological state of patients were also extracted from the raw input data. This dataset was next divided into 2 parts: a training dataset containing 66% of the objects and a testing dataset containing the rest of data. These prepared datasets were used, after noise reduction, as input for the attribute selection methods and their results were verified afterwards.

A double verification of the results was performed. For synthetic verification, we used our implementation of the rule-induction system, which is based on the Rough Set MLEM2 algorithm. The biggest challenge was the practical verification of generated results. This part of the validation of the selected attributes and their clinical importance was performed by the cardiology experts experienced in pacemaker implantation from the Electrocardiology Department of the Medical University of Silesia. To help them with the analysis, the results were presented as decision trees, which are an integrated part of our software. We used a J48 decision tree (C4.5 release 8) – a TDIDT (top-down induction of decision trees) approach derived from Quinlan's ID3 induction system [6].

3. Results

The results of the feature selection achieved for classifying implanted pacemaker types: DDD, VDD and SSI (AAI and VVI) were analysed.

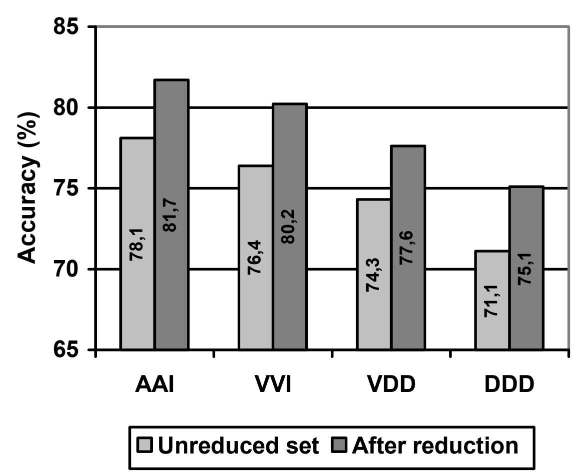

Figure 2. Comparison of the accuracy of decision rules for various types of pacing depending on the reduction of attributes

For the DDD type it was possible to reduce the initial set of 13 attributes to 5 attributes, which at the end effectively reduced the number of generated decision rules from 252 to 15-34 (the exact number depends on the reduction method). The generated decision rules showed better (74.8-75.6%) recognition accuracy than the unreduced set of attributes (71.1%). The following attributes were selected: atrioventricular block, paroxysmal tachycardia, atrial fibrillation and flutter, chronic ischemic heart disease and sinus node dysfunction. In DDD cases chronic ischemic disease, whose presence has no influence on the decision about pacemaker implantation and usually is completely independent from heart rhythm disorders, was the most problematic.

For VVI we reduced the initial number of attributes to 4 so that it was possible to reduce the number of generated decision rules from 253 to 12-23. Recognition accuracy for the reduced sets of attributes was between 79.9 and 80.9% (for the unreduced set 76.4%). The following attributes were selected as key attributes for choosing VVI pacemakers: atrioventricular block, paroxysmal tachycardia, atrial fibrillation and flutter and sinus node dysfunction. The number of reduced attributes for VVI was 5, which also reduced the number of decision rules from 57 to 15. The recognition accuracy was similar to the unreduced set of attributes (92.2-93.1%). No attribute was chosen which from medical point of view might cause any controversies. The very high recognition accuracy for the VVI type was the result of an over-fitting effect, where due to class distribution (noticeable in more patients without VVI pacemaker) the generated decision rules classified more new cases into the non-VVI category. Therefore, synthetic recognition accuracy for these cases must be considered carefully. Such effects limit the value of synthetic tests in the cardiological domain and this is why we always validate the results with domain experts.

The key element in our system is the practical reliability of the results. Decision tree algorithms were used to help experts verify the results. An example of this kind of tree is presented in Figure 3.

4. Discussion and conclusions

In 2006 during the annual conference Computers in Cardiology in Valencia, Spain, we presented a new method of data preparation for cardiological decision support [7]. During this year main aim of our team was preparation of the next element of system – new feature selection methods for cardiology. There is such a need because our earlier experiments showed that this step plays a key role in the accuracy of complex decision support system. In the study presented in this paper we show the results of our ideas of using feature selection for medical datasets. These sets contain a lot of noise and redundant information, which should be filtered out before the next machine learning algorithms are used [8].

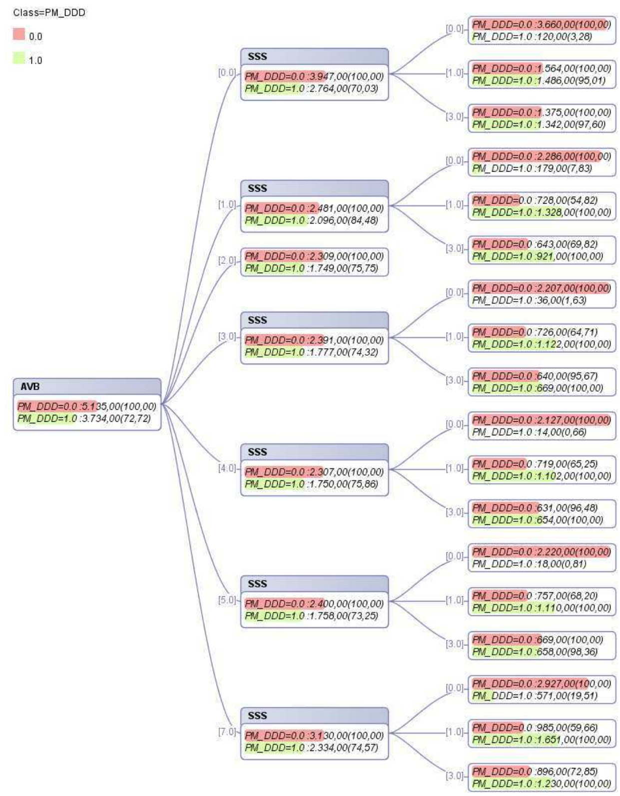

Figure 3. An example of a simplified decision tree (2 attributes, 2 decision classes)

An additional advantage of feature selection is the reduction of the search space, which, as presented in this paper and our entry research, reduces the number of decision rules (sometimes by factor of 10) without compromising prediction accuracy [9,10]. This fact is very important in the medical domain where achieved results must be explainable and verifiable by experts. In this paper we showed results for two feature selection algorithms: CFS and the Chi-square test both of which belong to the filter category. Filter algorithms mainly have two advantages over Wrappers: they require significantly less computational effort (very important for analysis of large datasets) and the achieved results do not depend on a specific learning algorithm.

In our experiments we selected subsets of attributes both from original training sets and from training sets after applying some noise reduction algorithms (over 1800 combinations for DDD, AAI, VVI and VDD). The selected subsets were then used to generate decision rules using the MLEM2 algorithm.

In all the results presented in this paper, it was possible to reduce the initial set of 13 attributes to about 4-5 attributes (more than a 60% reduction). Elimination of unnecessary attributes was the reason for the small number of decision rules – reduction by a factor of 6-10. This number shows the importance of the attribute reduction process. Each unnecessary and/or noisy attribute that must be taken into consideration by a rule generation algorithm extends the search space and in the end increases both the number of rules and their complexity. In order to reduce the number of attributes, several ranking methods were proposed. These methods measure attribute dependency to evaluate the value of an attribute. In this paper, we used two methods for attribute selection CFS and the Chi-square test. CFS uses symmetrical uncertainty to filter out irrelevant and redundant attributes, whereas the Chi-square test computes the statistical significance for bivariate tabular analysis (crossbreaks). Our experiments, together with expert validation, showed that both algorithms select a similar number of attributes but the Chi-square test selects attributes that are more important from a medical perspective. Nevertheless, CFS is an interesting algorithm because of its ability to evaluate a complete set of attributes and its calculation speed, which makes it interesting for a quick estimation of the number of necessary attributes.

Additionally presentation of the results is very important. Our initial experiments with decision trees showed that this method is fully acceptable to experts and significantly decreased the time needed for validation.

The number of patients with implanted pacemakers increases year by year, and additionally not only new algorithms, but also new biventricular pacemakers for cardiac resynchronization therapy (CRT) are introduced on the market. This is the conceptual evolution of classic stimulation and pacemakers. Its special feature is the presence of an additional lead that is implanted via the coronary sinus to the lateral or the posterolateral vein of the heart. Qualification of the patients for these types of pacing is more complicated which can mean that the methods presented in this paper can be even more useful in the future through the support of the process of programming.

Although choosing the best type of pacing in most cases is rather simple, new guidelines and types of devices can be a serious problem even for doctors experienced in this field. This refers not only in qualifying patients for implantation, but also after the patients have implanted pacemakers. First results show a high accuracy and the potential usefulness of these methods in clinical practice.

4.1. Conclusions

Based on the results we extracted the following conclusions:

1. A hybrid method of feature selection that combines the advantages of both algorithms can be an interesting solution of the feature selection problem in the electrocardiological domain.

2. A high reduction ratio both for the number of attributes and the number of rules was achieved.

3. A small number of understandable rules and the presentation of the results in a graphical form of decision trees were successfully validated by the experts.

4. The usefulness of the presented method in clinical practice was confirmed.

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Address for correspondence

Computer section	**Cardiological section**
Grzegorz Ilczuk	Rafal Mlynarski
Heuweg 12A	Klinika Elektrokardiologii
91334 Hemhofen, Germany	ul. Ziolowa 45/47
email:	Katowice 40-635, Poland
Grzegorz.Ilczuk@Ilczuk.com	email: joker@mp.pl