Computer aided diagnosis for cardiovascular diseases based on ECG signals : a survey

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Computer aided diagnosis for cardiovascular diseases based on ECG signals: A Survey

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Abstract

The interpretation of Electroencephalogrphy (ECG) signals is difficult, because even subtle changes in the waveform can indicate a serious heart disease. Furthermore, these waveform changes might not be present all the time. As a consequence, it takes years of training for a medical practitioner to become an expert in ECG based cardiovascular disease diagnosis. That training is a major investment in a specific skill. Even with expert ability, the signal interpretation takes time. In addition, human interpretation of ECG signals causes interoperator and intraoperator variability. ECG based Computer-Aided Diagnosis (CAD) holds the promise of improving the diagnosis accuracy and reducing the cost. The same ECG signal will result in the same diagnosis support regardless of time and place. This paper introduces both the techniques used to realize the CAD functionality and the methods used to assess the established functionality. This survey aims to instill trust in CAD of cardiovascular diseases using ECG signals by introducing both a conceptional overview of the system and the necessary assessment methods.

1 Introduction

Cardiovascular diseases are a global public health problem, because they contribute about 30% of global mortality and 10% of the global disease burden [1, 2, 3]. In 2005, about 58 million deaths occurred worldwide, 17 million of these mortalities were due to cardiovascular disease [4, 5, 6]. According to heart disease and stroke statistics, the adjusted populations attributable to cardiovascular disease mortality are 40.6% for high blood pressure, 11.9% for insufficient physical exercise, 13.2% for poorly balanced diet, 13.7% for smoking and 88% for abnormal glucose levels [7]. In other words, cardiovascular diseases are linked to poor lifestyle choices, such as increased intake of fat, smoking, physical inactivity and alcohol consumption [8]. Despite numerous campaigns and public education efforts, these bad lifestyle choices are on the rise. For example, obesity and the prevalence of obesity has increased dramatically worldwide over the last decades and it has now reached epidemic proportions [9]. Furthermore, in America 21.3% of men and 16.7% of women, older than 18 years, continue to smoke. While the number of patients with cardiovascular diseases is receding in several high income countries, low and middle income nations have seen a rise in the occurrence, where 82% of cardiovascular disease deaths occur in both genders equally [10].

In disease prevalence studies, the World Health Organization (WHO) defined cardiovascular diseases from symptoms, ECG abnormalities, and enzymes [11]. Amongst these diagnosis methods, ECG has the potential to deliver cost savings, because the signal acquisition is non invasive and a measurement setup requires only medium skilled labor. However, ECG by itself is often insufficient to diagnose cardiovascular diseases, such as acute coronary syndrome or acute myocardial infarction. It is important to improve the accuracy of ECG based diagnosis, because it reduces the need for more expensive diagnosis tools. Furthermore, a higher accuracy allows us to detect cardiovascular diseases earlier. Traditionally, improving the diagnosis accuracy requires more training for the screening medical practitioner. However, training is a considerable reoccurring cost factor.

CAD systems hold the promise of reducing cost and at the same time improving the accuracy of ECG based diagnosis. The cost reduction arises from the fact that human labor is replaced by machine work. The accuracy improvements result from a range of beneficial trends, chief amongst them is progress in the relevant areas of science and technology. In this introduction to CAD for cardiovascular disease we explore the techniques used to create the systems. We focus on statistical performance assessment methods, which are applied during the system design phase, because an understanding of these methods enables us to judge the CAD system quality. The ability to assess CAD systems for cardiovascular diseases instills trust in these systems. Trust, but not blind reliance, is needed to work with these systems in order to realize the promise of improving cardiovascular diagnosis while at the same time reducing the cost.

The article is organized as follows. Section 2 introduces the materials and methods used to construct a CAD system for cardiovascular diseases based on ECG signals. The system assessment methods take center stage of our discussion, because the assessment results shape both the construction of the CAD system and subsequently the acceptance of the physical problem solution in a practical setting. Section 3 provides insight into practical performance reporting and analysis. Practical settings and limitations are also covered in the discussion section. Section 5 concludes the introduction to CAD for cardiovascular diseases based on ECG signals.

2 Materials and methods

All CAD systems aim to provide diagnosis support for medical practitioners by suggesting a possible diagnosis [12]. The CAD system reaches the diagnosis through a decision making process. In general, the decision process is based on physiological measurements or medical images [13]. The output ranges from simple disease or non-disease classifications to the sophisticated detection of specific diseases. The decision support quality is an important criteria for selecting a CAD system. The quality is evaluated based on statistical performance measures throughout the CAD system design phase. Hence, in order to judge the quality of a CAD system it is necessary to understand the design principles which lead to the creation of such systems. This section provides the necessary background to judge and select CAD systems.

To explain CAD systems for cardiovascular diseases based on ECG signals in detail, we adopt the design perspective. Fundamentally, the design is structured into an offline and an online system. The offline is used to evaluate and select the best algorithm structure. The selected algorithm structure is employed in the online system where it servers as diagnosis support system. Figure 1 shows an overview blockdiagram of the online and the offline systems. Both the online and offline systems are modeled as an algorithm chain. The algorithm chain starts with preprocessing and the feature extraction. These initial steps condition the ECG signals for classification. As such, the classification results constitute the decision support for medical practitioners. The next sections provide a brief overview of the individual concepts and methods used in both online and offline systems.

2.1 ECG signals

ECG signals represent the electrical activity of the heart and they can be used to investigate cardiac health [14]. The offline system deals with known or labeled ECG datasets. The label indicates whether the signal was measured from a diseased patient or from a normal control. For more sophisticated systems the label indicates one of multiple diseases. Datasets with the same label form one signal class. For example, ECG signals from normal controls (Normal Sinus Rhythm (NSR)) form the NSR signal class [15]. ECG signals taken from patients with Atrial

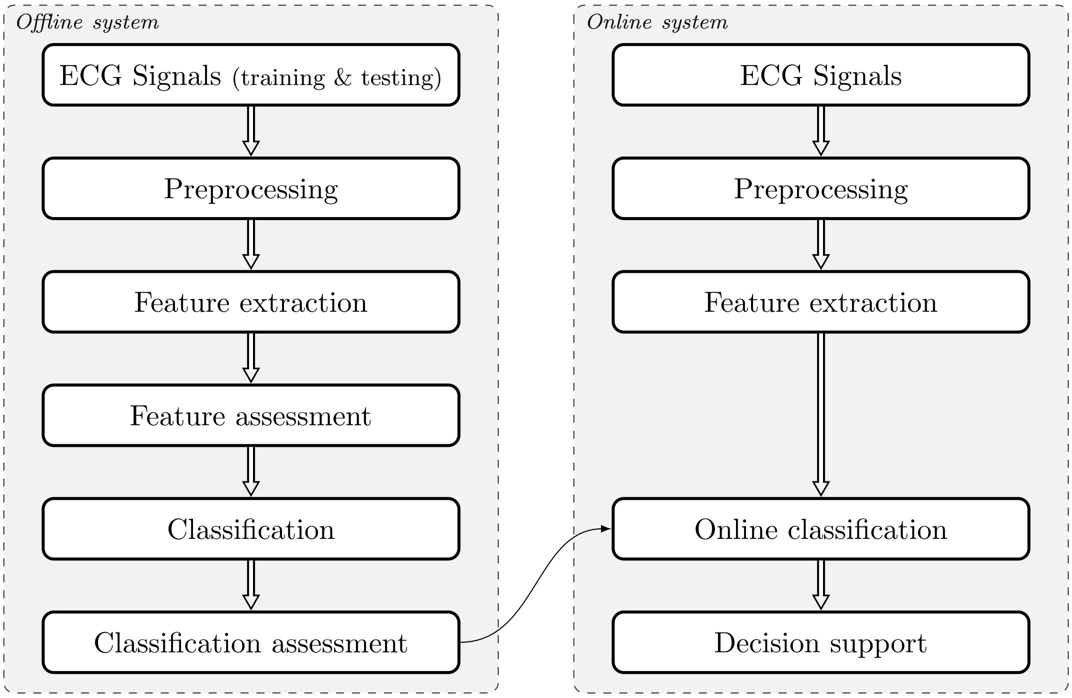

Figure 1: Overview block diagram of CAD systems for cardiovascular diseases based on ECG signals.

Fibrillation (AF) form the AF signal class. Finally, signals taken from patients with Atrial Flutter (AFL) form the AFL signal group. The task of the CAD system is to differentiate the individual signals and classify them into one of the signal classes. For the example above, each ECG signal is classified into one of the three distinct signal classes $\{NSR, AF, AFL\}$. Apart from these three signal classes, CADs were developed tor Atrial Tachycardia (AT), Ventricular Tachycardia (VT), Ventricular Fibrillation (VF), Ventricular Flutter (VFL), Premature Ventricular Contraction (PVC) and general Cardiovascular Disease (CVD). Beat specific labeling included Non-Ectopic Beat (NEB), Supraventricular Ectopic Beat (SVEB), Ventricular Ectopic Beat (VEB), Fusion Beat (FB) and Unclassified Beat (UB).

Knowing the signal labels allows us to assess the algorithms used in the offline system. The individual algorithms and their assessment methods are discussed in the subsequent sections. Given the importance of labeled data for the design of CAD systems, the aspect of of data volume, number of classes and performance are vital. Data volume describes the number of labeled ECG data sets. In general, more data sets leads to a statistically stronger evaluation. Data variety referrers to both the number of signal classes and the variety of signals belonging to the same class. For classification evaluation problems, the variety of signals within the class is critical, because only if the variety of the labeled data sets matches the variety of practical ECG signals, measured in a clinical setting, then the assessment results are credible and indeed the CAD system performs as expected in a practical setting. Data performance refers to the data quality. Similar to the data variability, the data veracity of the labeled data set must match the expected data veracity in a practical setting, because a mismatch might render the CAD performance assessment incorrect. The data veracity is difficult to estimate, but in general the quality of labeled data is high, because these datasets were measured by experts in medical centers.

Labeled ECG datasets are a prerequisite for the design and assessment of CADs for cardiovascular diseases. PhysioNet is a de facto standard resource for research on cardiovascular CAD [16]. Having such a standard research makes the individual performance results more comparable, but more data variety is required to increase the reliability of the implemented systems.

2.2 Preprocessing

The ECG signals are measured with electrodes on the body surface. Therefore, they are often contaminated by various kinds of unwanted signal components, such as power-line interference, baseline wander, electromyographic noise, electrode motion artifacts and so on [17]. Humans can deal with noisy signals and experienced medical practitioners have the ability to spot and subsequently ignore ECG signal artifacts. In contrast, these unwanted signal components have a negative impact on the ability of the CAD system to provide adequate diagnosis support. Preprocessing aims to reduce the negative effect of unwanted signal components. The reduction is established through filtering or signal removal [18, 19].

2.3 Feature extraction

The feature extraction step is necessary, because the classification algorithms fail to process ECG signals directly. To be specific, the most effective classification algorithms can only deal with a very limited amount of parameters, practical knowledge suggests that the number of parameters should be kept at a minimum [20]. Martis et al. provide a detailed review of feature extraction methods [8].

Feature extraction methods can be classified as either linear and nonlinear. In general, linear methods are old, they are based on time and frequency analysis techniques [21]. The following list provides names, linear feature extraction methods and references to the CAD systems which employed them.

- RR interval – The RR-interval measures the time duration of a cardiac cycle. [22, 23]
- Spectrum – In the area of feature extraction, a spectrum denotes the result of a frequency domain analysis [24]
- Lorenz plot – A graphical representation of a cumulative distribution function of an empirical probability distribution of a quantity of interest. For example, the hear rate variability is such a quantity of interest [25]
- First and second order statistics – Mean and variance [26]
- Discrete Wavelet Transform (DWT) – This feature extraction technique is closely related to spectrum techniques. Spectrum techniques provide only frequency restitution, whereas DWT provides both time and frequency resolution [27, 28, 27, 29]
- Independent Component Analysis (ICA) – The technique separates multivariate signals into their additive subcomponents [27, 15, 28]
- Principal Component Analysis (PCA) – The statistical procedure is based on orthogonal transformation which produces linearly uncorrelated parameters known as the principal components [30, 29, 28, 31, 32]
- Linear Discriminant Analysis (LDA) – Yields features that characterizes two or more signal classes [28]
- Discrete Cosine Transform (DCT) – Spectrum technique based on cosine waves [15, 33]

Nonlinear methods are based on the more recent concepts of chaos and fuzzy logic [34, 35, 36]. The novelty of these methods is reflected in the fact that only a few recent CAD systems employ them, as indicated in the following list.

- Fractal characteristics – From chaos theory. Used to describe the fractal nature of a signal [37, 38]
- EM Clustering – The expectation–maximization (EM) algorithm constitutes an iterative method that estimates parameters in statistical models [39]
- Higher Order Statistics – Statistical measures beyond mean and variance [31, 32]

2.4 Feature assessment

The feature quality depends on the ability to discriminate the minute ECG signal changes that indicate a specific disease [40, 14]. Feature assessment aims to quantify the ability to detect these signal changes correctly. The feature assessment serves two purposes:

1. Feature assessment results can be used for feature selection. There are numerous linear and nonlinear feature extraction methods in existence, however the classification algorithms work effectively with a minimum number features. Hence, not all features can be used for classification and a selection process is necessary to find the best features. Such a selection process is based on the feature assessment [41].
2. Instill trust in the CAD system for cardiovascular diseases based on ECG signals. That is a very important exercise, because a system design needs a consistent performance where good feature assessment results lead to good classification results [33]. Excellent classification results conflict with poor feature assessment results, therefore such systems are less trustworthy.

A popular method for feature assessment is a statistical test method called Analysis Of Variance (ANOVA) [42, 41, 43, 44]. The method establishes the similarity within signal groups and the distinctiveness amongst signal groups. As such, the signal groups are established with labeled datasets. The ANOVA algorithm is aware of the individual signal groups and it checks the parameter value distribution. The checking principle is based on the so called *null hypothesis* which postulates that the parameter distribution is random. The algorithm expresses the null hypothesis validity with the p-value. A quality feature causes the ANOVA algorithm to reject the null hypothesis, because the parameter clusters are not random. As a consequence, a good feature will have a low p-value. For clinical trials, a p-value of 0.05 is considered to be clinically significant. However, for CAD, we regularly see features with p-values below 0.0001.

The most important characteristic of the offline system is the fact that the individual features compete, i.e. the features are ranked and subsequently they are selected according to their ability discriminate the signal groups [45, 46]. One way of feature ranking is based on the ANOVA test results. The feature with the lowest p-value is ranked fist, the feature with the second lowest p-value is ranked second etc. Only the highest ranking features are selected as elements of the feature vector, which is fed into the classification algorithms.

2.5 Classification

The idea behind automated classification algorithms is to learn the characteristics of different signal classes based on known feature vectors [47, 48]. The acquired knowledge is used when an unknown feature vector is identified. As such, the identification process assigns a label to the unknown feature vector. The method of using known data to train the algorithm is known as supervised learning [42]. The following list details examples of supervised learning algorithms and it provides a reference to the CAD systems which use them:

- Support Vector Machine (SVM) – The coordinates of the feature space are transformed such that decision borders become straight lines, i.e. the signal classes a linearly separable. For nonlinear data, nonlinear kernel functions are used [49, 28, 29, 31, 32].

- ADABoost – The results of numerous weak learners is combined to form a strong decision [49].
- Artificial Neural Network (ANN) – The algorithm mimics brain functionality [50, 15, 29, 32, 31].
- Gaussian Mixture Model (GMM) – The algorithm decides to which subpopulation in input vector belongs [28].
- Decision Tree (DT) – The decision making algorithm is based on a tree like graph that structures a continuum of binary questions [51, 52, 15, 24].
- Fuzzy classifier – Based on grouping known elements into fuzzy sets and identifying unknown input by mapping it to one of the previously (training phase) identified sets [52, 37, 38, 27].
- K-Nearest Neighbour (K-NN) – The majority of neighboring known signal points decides the signal class of an unknown input [15, 28, 31].
- Probabilistic Neural Network (PNN) – Refinement of an ANN [28, 33].
- Classification And Regression Tree (CART) – Used to construct prediction models form ECG data [53, 31]
- Random Forest (RF) – Ensemble learning algorithm [31]
- Threshold – Binary decision based on a threshold value [25, 26, 22, 23].

The classification algorithms were introduced with just a brief discussion of the functionality. The variety of classification algorithms, used in practical systems, indicates that there is no consensus which method is works best to classify the features extracted from ECG signals. Hence, a wide range of classification algorithms should be tested in the offline system. The CAD systems, which used these classification algorithms to identify cardiovascular diseases, were cited.

2.6 Classification assessment

In the offline system, the classification results are assessed based on the labeled datasets. The assessment helps us to select the most appropriate classification algorithm for online system [54]. For a two class problem (normal and abnormal) individual measures are briefly explained below:

- True Negative (TN)=Number of normal data classified as normal.
- False Negative (FN)=Number of abnormal data classified as normal.
- True Positive (TP)=Number of abnormal data correctly classified as they are.
- False Positive (FP)=Number of normal data classified as abnormal.
- Accuracy (A)=(TP + TN) / (TP + FN + TN + FP).
- Sensitivity (Se)=TP / (TP + FN).
- Specificity (Sp)=TN / (TN + FP).

Accuracy, sensitivity and specificity are basic performance measures, used to assess classification algorithms. Apart from these basic assessment methods, a Receiver Operating Characteristic (ROC) curve may be used. The curve is created by plotting the TP rate against the FP rate at various threshold settings. Having such an ROC plot allows us to assess the classification quality and we can set the threshold value son that the highest classification accuracy is achieved [55, 56].

A fundamental problem of supervised learning is the arbitrary split of the labeled datasets into testing and training data, because that split, to some extent, influences the classification accuracy. k-fold cross-validation aims to overcome the dependency by sub-sampling the labeled dataset into k disjoint sets. $k-1$ sets are grouped together to form the training set. The remaining fold is used to test the classifier. There are k runs and for each run a different fold is used. Performance measures, such as A, Se and Sp, are computed after each run. In a last step, the average over all individual results is calculated for each performance measure. As a consequence, k-fold cross-validation results are less biased compared to traditional classification assessment methods [15].

2.7 Online system

The online system contains preprocessing, feature extraction and classification algorithms [57]. Statistical feature and classification assessment is not possible, because in the online system all the ECG signals and indeed the the resulting feature vectors are unknown, i.e. no predefined labels exist for the ECG signal. The online system classifies a particular ECG signal as belonging to specific signal group. That classification can be a valuable support for the diagnosis of a patient.

The quality of the diagnosis support depends on the algorithms and parameters used to process the ECG signal and to establish the classification. Therefore, the design process, structured through the offline system, is so important for the practical relevance of the deployed CAD system. To be specific, once the online system is deployed, the diagnostic quality is established through the assessment methods used in the offline system.

Using softprocessing methods in the online CAD system has the advantage of updating the system. It is expected that the algorithms, used to discriminate individual cardiovascular diseases will improve. Furthermore, the labeled ECG data volume, number of classes and performance is expected to increase over time. As a consequence, the algorithm structure, which underpins the diagnostic support, gets better, i.e. accuracy, sensitivity and specificity of the offline system will increase. In addition to these improvements, the assessment results are more credible, because they are based on data which is closer, in a statistical sense, to the ECG signals measured in a practical setting. Regular updates of the online system ensure that the CAD system performance continuously improves without additional effort from the practicing medical doctor.

3 Practical performance reporting and analysis

The performance of CAD systems is established with statistical measures. Credible system design teams use the performance measurement results to compete with published results from other design groups. Only the best performing CAD systems for cardiovascular diseases will be implemented, that ensures the best possible diagnosis support for medical practitioners. Table 1 provides an example on how the performance measurement results are compared. The last row is usually reserved for the results of the CAD system under discussion, because such a setup makes it easy for the reader to compare the performance assessment results.

Table 1: Performance summary of different CAD systems for cardiovascular diseases. * indicates that the labeled datasets were specified as database entries.

Name	Method	Labeled datasets	Quality
Cerutti et al. [37]	AR model on RR intervals	NSR and AF	Se=96%, Sp=81%
Slocum et al. [24]	Atrial activation	NSR(81) and AF(74)	Se=62%, Sp=71%
Hu et al. [58]	Mixture of experts	SVEB and NSR	94.0%
Tatento et al. [23]	K-S test on RR intervals	NSR(95879) and AF(11589)	Se=91%, Sp=96%
Wang et al. [38]	Multifractality	AF(60), VF(60) and VT(60)	AF A=99.4%, VF A=97.2%, VT A=97.8%
Logan et al. [22]	Variance in RR intervals	NSR(–) and AF(–)	Se=96%, Sp=89%
de Chazal and Reilly [59]	Heartbeat interval	SVEB, non-SVEB	A=97%, Se=77.7%
Inan et al. [60]	DWT and timing interval	PVC, NSR from MIT/BIH arrhythmia database	95.2%
Sarkar et al. [25]	RR interval deduced features	AF(422 h) and AT(2000 h)	Sp=94%
Chao et al. [26]	Delta RR interval difference curve	AF(6599599) and NSR(1729629)	Se=96.1%, Sp=98.1%
Fahim et al. [39]	Compressed ECG	VF(30*), VFL(16*), PVC(1*) and AF(2*)	A=97%
Martis et al. [29]	Segmentation, re-sampling	Normal(10000) and abnormal(24989)	A=98.11%, Se=99.90% and Sp=99.10%
Jovic et al. [49]	Linear and nonlinear features (in total 56)	Nine classes (total 109000)	A=85.63%
Giri et al. [28]	Variance in RR intervals	NSR(16 $\times$ 15 min) and CVD(16 $\times$ 15 min)	A=96.8%, Se=100% and Sp=93.7%
Martis et al. [32]	Segmentation, re-sampling	Normal(10000) and abnormal(24989)	A=94.52%, Se=98.61% and Sp=98.41%
Martis et al. [33]	Segmentation, re-sampling	NEB(90580), SVEB(2973), VEB(7707), FB(1784) and UB(7050)	A=99.52%, Se=98.69%, Sp=99.91%
Martis et al. [61]	Time domain ECG amplitude	NSR, AF and AFL	Se=100%, Sp=99.33%, A=99.42%
Faust et al. [30]	PCA features	NEB(90547), SVEB(2972), VEB(7704), FB(1783) and UB(7070)	A= 96.4%, Se=96.3% and Sp =98.4%

Table 1: (continued)

Name	Method	Labeled datasets	Quality
Martis et al. [31]	Segmentation, re-sampling	Normal(10000) and abnormal(24989)	A=93.48%, Se 99.27% and Sp=98.31%
Martis et al. [32]	Cumulants	NSR, AF and AFL	Se=100%, Sp=99.22%, A=99.50%
Martis et al. [62]	Segmentation, re-sampling	NSR(641), AFL(887) and AF(855)	A=97.65%, Se=98.16% and Sp=98.75%
Jenny et al. [27]	DWT, ICA	NSR(1000) and PVC(1000)	A=80.94%, Se=81.10% and Sp=80.1%
Martis et al. [15]	ICA on DCT	NSR (1200), AF(887) and AFL(855)	Se=99.61%, Sp=100%, A=99.45%

Column two of Table 1 indicates the methods used for feature extraction. For CAD system design, the feature extraction methods are more important than the classification algorithms. Therefore, detailing these methods is more beneficial for comparing the individual systems.

Column three of Table 1 details the labeled dataset which is used to create and assess the reviewed CAD systems. There are three different ways to report the labeled dataset which is used to design and assess the CAD system.

Column four of Table 1 reproduces the reported performance measure results. The most important performance measure is the classification accuracy, because it provides a good indication of the overall system performance. As a consequence, the CAD systems are ranked in the order of their classification accuracy. However, such a ranking should be understood in terms of what is possible, i.e. the ranking answers what is the best possible classification accuracy. An in-depth discussion is required relates the best possible classification performance to the a new method, especially when the classification performance is lower than the best reported performance.

4 Discussion

The promise of CAD for cardiovascular diseases based on ECG signals to provide diagnostic support with less capital and time investment. CAD in healthcare applications can help in automated decision making, visualization and extraction of hidden complex features to aid the clinical diagnosis process. The main component to realize that promise is well earned trust. Trust comes from understanding the technologies which underpin the CAD systems. Therefore, this review has focused on providing the reader with a broad overview of the methods used. The concept of offline and online systems is instrumental for an informed discussion on these topics. Assessment is an integral component of trust, hence both feature and classification assessment strategies are introduced in the Materials and Methods section.

Apart from the design methods, there is also a social aspect to CAD for cardiovascular diseases. In this section we explore social benefits of CAD systems by discussing their relationship to the healthcare divide between urban centers and rural areas. The benefits come from cost savings and ease of use, as discussed in Section 4.2. In Section 4.3 we explore the limitations of and risk associated with CAD systems.

4.1 Bridging the heath-care divide with CAD systems

At the time of writing, there are more doctors and medical staff available in urban centers than in rural areas. That problem is especially prominent in of developing countries. Furthermore, urban centers host advanced diagnostic machines, hence there are also the specialists who operate them. As a consequence, rural people don't have access to healthcare facilities. Investing into advanced medical technologies and employing more doctors in charitable medical hospitals in rural areas might not be economically feasible, especially in developing and third world countries. Science and technology can to tackle such a complex, large scale problem in an objective, logical, and professional way. The solution must involve a collaborative effort, which is based on a team of experts, that works on the health care problem holistically. On the technical level, communication and networking can help economically middle class people and even some rural poor have access to internet and mobile communication systems. These systems can be used to communicate ECG signal data to urban centers with diagnostic expertise. In urban centers, CAD systems can help to diagnose cardiovascular diseases in a nascent stage [63].

Even with the clarity on design and realization of ECG based CAD systems some limitations and shortcomings still remain. The main limitation comes from the fact that most studies on CAD for cardiovascular diseases are based on a small number of classified ECG signals. Having only a small dataset to test the features implies that the statistical significance of the feature assessment can be doubted. A small number of ECG signals poses an even greater problem for the classification step, because the set is split into subsets for training and testing. By splitting the known dataset, we reduce the variability within the sets further, hence the classifier is neither trained nor tested with all the available information. The cross-validation techniques try to reduce the negative effects of these shortcomings. But, even cross-validated classification results are ultimately limited by the number and performance of the known dataset.

4.2 ECG versus chemical measurements

ECG and troponins are the current diagnostic tests available for clinical assessment of the heart [64, 65]. These tests improve clinical practice by helping to identify patients with acute symptoms who are at high risk. Furthermore, these tests help in selecting patients who are likely to benefit from an early invasive intervention. Combining sensitive cardiac troponin assays with clinical assessment and ECG will reduce the number of patients for whom the diagnosis is uncertain after the first cardiac troponin measurement. IF the cases are still uncertain, continuous ECG monitoring and serial blood sampling might be necessary. In the long run, electronic measurements are always more cost efficient than chemical measurements [11]. Increasing the early diagnostic accuracy, are likely to result in substantial cost sayings [66]. The combination of ECG and troponins overcomes the low sensitivity of ECG alone [67].

4.3 Design faults in CAD systems

A big and growing problem for CAD is system failures caused by weak design approaches. As such, the error probability of digital systems is astonishingly low, under normal conditions, a digital system exhibits an error once in every 10^{23} operations [68]. However, digital processing systems, such as CADs, fail much more often than the error probability suggests. Root cause analysis shows that design problems cause these additional system failures. The argument which relates design problems to system failures starts with the following observation. In terms of computer science, the online system is designed as a network of algorithms. To be of practical use, such networks are quite complex [69]. Unfortunately, the system complexity is positively correlated with the design error probability. In other words, complex systems tend to have much more design errors. It is impossible to find design errors through testing, because reasonably complex CAD systems can be in one of several million system states and it is impractical to test the stability of all system states [70]. As a consequence, refined design methods are required to minimize the design errors. In future, when CAD systems become even more pervasive and more human wellbeing depends on the correct functionality of these systems. Hence, we have to limit the impact of design and other errors in the online system. For example through fault tolerance, contingency and backup systems [71].

5 Conclusion

This paper gives an introduction to CAD for cardiovascular diseases based on ECG signals. The CAD systems provide diagnosis support for medical practitioners through signal processing and classification algorithms. The system design is based on the concept of offline and online systems. The offline system uses performance assessment methods to select the best algorithm structure. Only when the selected algorithms are used in the online system it provides decision support for medical practitioners. A direct consequence from having the concept of online and offline systems is that the diagnosis support quality is established with the offline system. Therefore, quality measures, such as statistical feature tests and classification performance measures, are of paramount importance.

Before the widespread deployment of CAD systems for cardiovascular diseases, we have to establish trust in these systems. A major component to build trust is an an explanation on how the system works. In this paper we have tried to explain the design and test principles of CAD systems for cardiovascular diseases based on ECG signals. The design principles are sound, because through internal and external competition a designer thrives to find the best possible algorithm structure for the given task. Issues remain with the availability of reliable datasets for testing. Furthermore, the engineering quality of these systems is an issue, therefore it is not (yet) recommended to trust CAD systems blindly, current systems can only provide diagnosis support. Even with these limitations, CAD based on ECG signals can reduce the workload of medical practitioners dramatically. As a direct consequence, screening of ECG signals will help to detect many cardiac diseases early and save life. Therefore, such systems will aide cardiovascular disease diagnosis, treatment monitoring and drug efficacy tests.

CAD systems will get more and more important in the future, because all physiological measurements, such as ECG, will be digital. The digital content is a treasure trove for data mining and artificial decision making systems. Apart from the general applicability of these techniques to large data sets, working on the particularly well known ECG signals has the advantage that there are labeled datasets available. However, more data is needed to improve the CAD systems. In future that shortage will be overcome and the offline systems will become like robots crawling through enormous amounts of data and optimizing the diagnosis support strategy. The improved diagnosis support strategies will be made available as updates for the diagnosis support systems. So, the latest research, based on the most comprehensive data, will be available in the most user friendly form – a new update will work in a familiar CAD system.

6 Acronyms

A Accuracy
AF Atrial Fibrillation
AFL Atrial Flutter
ANN Artificial Neural Network
ANOVA Analysis Of Variance
AT Atrial Tachycardia
CAD Computer-Aided Diagnosis
CART Classification And Regression Tree
CVD Cardiovascular Disease
DCT Discrete Cosine Transform

DT	Decision Tree
DWT	Discrete Wavelet Transform
ECG	Electroencephalogrphy
FB	Fusion Beat
FN	False Negative
FP	False Positive
GMM	Gaussian Mixture Model
ICA	Independent Component Analysis
K-NN	K-Nearest Neighbour
LDA	Linear Discriminant Analysis
NEB	Non-Ectopic Beat
NSR	Normal Sinus Rhythm
PCA	Principal Component Analysis
PNN	Probabilistic Neural Network
PVC	Premature Ventricular Contraction
RF	Random Forest
ROC	Receiver Operating Characteristic
Se	Sensitivity
Sp	Specificity
SVEB	Supraventricular Ectopic Beat
SVM	Support Vector Machine
TN	True Negative
TP	True Positive
UB	Unclassified Beat
VEB	Ventricular Ectopic Beat
VF	Ventricular Fibrillation
VFL	Ventricular Flutter
VT	Ventricular Tachycardia
WHO	World Health Organization

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