ABSTRACT
This paper presents an overview of different algorithms for the detection of characteristic points and intervals in electrocardiograms (ECG) on basis of literature research. The ECG is an important tool in the diagnosis of heart diseases since the shape of the ECG curve contains vital information about heart conditions as for example its electrical conduction or muscle activity. Besides the conventional manual method automated extraction of ECG features is of major significance and benefit for the diagnosis of numerous malignant or even life-threatening cardiac diseases. For this reason, many algorithms which are based on various methods have been developed to support physicians in clinical practice. Here, we present several of these ECG feature extraction methods, focusing on the measurement of the QT interval, as well as two studies that compare algorithms of diverse degree of automation. Although current algorithms show good performance and mean errors which range in tolerable boundaries and are able to identify most of the characteristic points in ECG no gold-standard has been found so far. Remaining discrepancies between manual ECG analysis by human experts and automated algorithms give reason for further investigation.

General Terms

Keywords
QT interval, wavelet transform, ECG feature extraction, template stretching, template time shifting, superimposed median beat

1. INTRODUCTION
The analysis of the shape of ECG curves as well as the identification of relevant intervals between different waves is of major importance for the diagnosis of cardiac disorders. The ECG pattern contains a large amount of information about the functionality of the heart as for example its electrical conduction. Amplitudes of the different waves (P, QRS and T wave) as well as particular intervals in a cardiac cycle can indicate an underlying heart disease [5]. Manual beat-by-beat measurements of all characteristic points in every lead are impractical in routine clinical practice [4] especially for long-term ECGs. For this reason, automatic ECG feature extraction methods are of major relevance.

One significant ECG feature is the QT interval which has received much attention during the last 15 years [1] since its prolongation favours malignant cardiac arrhythmias and can lead to sudden cardiac death and is therefore an important cardiac risk factor [2,5]. In this context, numerous clinical studies are being conducted for example in the field of pharmacy since particular drugs can cause a prolongation of the QT interval and their effect to the heart has to be investigated [2].

Many algorithms and methods for automated ECG feature extraction and the QT interval measurement in particular have been developed. However, the formalisation of the QT interval measurement process remains insufficient and requires further investigation [1]. Especially the detection of the end of the T wave turned out to be challenging and current algorithms still differ from the ECG evaluation by human experts [2].

In this paper we present and discuss some of the commonly used methods for QT interval measurement. Moreover, conventional, semi-automated, and automated measurement methods are compared and we try to outline the current situation of automated ECG feature extraction on the basis of the QT interval measurement as an example.

Section 2 of the paper first gives a short overview of the basics of ECG. In the third section the functional principles of different methods for the ECG feature extraction are described and significant results of the validation of the algorithms are delineated. Two studies are presented in 3.5 and 3.6 that compare diverse methods of different degree of automation. Section 4 contains a short summary and discussion of the algorithms. The conclusions with respect to the achievements done already and further required research are given in section 5. Section 6 contains references to future work.

2. BACKGROUND
The ECG is the recording of the electrical activity of the heart and represents the depolarisation and repolarisation of the heart muscle cells and the heart chambers. The electrical signals from the heart are measured non-invasively using skin electrodes and appropriate electronic measuring equipment. The required data is converted into an ECG curve (written on paper or monitored electronically) which possesses a characteristic pattern. Deflections from this normal ECG pattern can be used as a diagnostic tool in medicine in the detection of cardiac diseases. More general information about the ECG can be found for example in [9,10,11].

Anatomically, the heart consist of four chambers (left and right atrium, left and right ventricle), blood vessels, as well as four valves that prevent backward flow within the heart. Another integral part of the heart is its electrical conduction system. The latter generates and conducts the electric stimulus for the muscle contraction and the associated produced cardiac output. [15]

The initial stimulus for each heart cycle is generated by specialised pacemaker cells. The primary pacemaker is called Sinus node. In case of a malfunction of the Sinus node there are a secondary and a tertiary pacemaker (AV node and Bundle of His) that ensure a reliable heart function. The Sinus node stimulus is
conducted through the atria via conduction pathways. Thereupon, the atria contract and pump blood into the ventricles. Atria and ventricles are separated by a thin isolating layer only discontinued by the AV node which triggers a short delay in the signal transmission until the process of pumping is completed. Afterwards, the AV node relays the stimulus through the Bundle of His, the Tawara branches and the Purkinje fibers. The latter are connected to the heart muscle cells of the ventricles that finally contract. A detailed description of the processes in the heart during a heart cycle is given in [12,15].

This delineated electrical activity caused by depolarisation and repolarisation of heart cells is measured using several interconnected skin electrodes. The differential voltages between in each case two of the electrodes (bipolar lead) respectively between one of the electrodes and a reference electrode (unipolar lead) are griped [10].

As a standard for ECG recording the 12-lead-ECG is commonly used. It consists of the standard bipolar limb leads (I, II, III, Einthoven leads), the augmented unipolar limb leads (aVF, aVL, aVR, Goldberger leads) as well as the standard precordial leads (V1-V6, Wilson leads). The three standard bipolar limb leads record the differential voltages between

- left arm and right arm (I)
- right arm and left leg (II) respectively
- left arm and left leg (III) [14].

To improve the angular resolution the augmented unipolar limb leads are measured additionally. Moreover, the precordial leads provide more beneficial information of the state of the heart and potential diseases. Figure 1 shows a simplified scheme of the lead directions of the Einthoven and the Goldberger leads on the basis of the Einthoven triangle: the vertices of the outer triangle characterise the locations of the limb electrodes on the left leg and the left and right arm. The arrows connecting the vertices (named I, II, III) describe the directions of the Einthoven leads. The Goldberger leads (aVF, aVL, aVR or rather augmented Voltage [foot, left arm, right arm]) are measured at right angle to the Einthoven leads. In Figure 2 the placement of the electrodes on the body is visualized.

Using the 12 lead ECG and the method of signal recording and processing it is based on we obtain a typical ECG pattern which is characterised by the sequence of several waves and complexes as can be seen in Figure 3.

The P wave characterises the propagation of the stimulation in the atria, whereas the QRS complex represents the stimulation of the ventricles. The following T wave marks the degeneration of this stimulation. So does the U wave which is, however, not present in all norm ECGs [8]. The RR interval as the time between two consecutive R peaks defines the cardiac beat cycle and can be used to calculate the heart rate [7].

Particularly significant for medical diagnosis are the amplitudes and the durations of the different waves as well as the intervals between them. Table 1 subsumes physiological durations of the different waves or intervals [8]. Deviations from these standard values can be a sign of a cardiac disorder. For this reason the correct and precise measurement of the intervals and the amplitudes are of major relevance and importance. The classical approach in heart diagnosis is the manual analysis and interpretation of the ECG pattern by a physician. Still today, this method is widely used because it proved its value and the implementation of alternatives is not easily made.
### Table 1: physiological durations of the characteristic components of an ECG pattern

<table>
<thead>
<tr>
<th>Wave or interval</th>
<th>guide value for the physiological duration in s</th>
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<tbody>
<tr>
<td>P wave</td>
<td>0.05 - 0.10</td>
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<tr>
<td>PQ interval</td>
<td>0.13-0.20</td>
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<tr>
<td>Q wave</td>
<td>&lt; 0.05</td>
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<tr>
<td>QRS complex</td>
<td>0.05 - 0.10</td>
</tr>
<tr>
<td>S wave</td>
<td>&lt; 0.04</td>
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<tr>
<td>QT interval</td>
<td>0.18 - 0.52</td>
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In this paper we focus in particular on the measurement of the QT interval which is of special relevance. The QT interval is the time between the onset of the Q wave and the T wave offset. It characterises the ventricular depolarization and repolarisation. Most commonly used for QT interval measurement is lead II. In addition, lead V5 and V6 are consulted frequently [13]. As can be seen in Table 1 the normal QT duration ranges between 0.18s and 0.52s. Other sources give the slightly different maximum values of 0.50s and 0.53s for the critical value for Torsade de Pointes [13]. There are different formulae as for example the Bazett-Formula for calculating the QTc which is the QT interval corrected for heart rate [13]. A significant shortening of the QT-interval can indicate many different cardiac disorders as for example the congenital long QT syndrome which is associated with an increased risk of atrial and ventricular fibrillation and sudden cardiac death. On the other hand, a prolongation of the QT-interval can be connected with ventricular arrhythmias like Torsade de pointes. The latter describes a special sort of polymorphic ventricular tachycardia (exceedance of the normal heart frequency) and can end in a life-threatening ventricular fibrillation as described in [13].

### 3. PRESENTATION OF DIFFERENT ECG FEATURE EXTRACTION METHODS

Especially during the last 15 years numerous algorithms for automated ECG feature extraction and QT interval measurement based on different methods have been developed. Commonly used are derivative or threshold methods. Mahmoodabadi et al [5,6] however, used a multi-resolution wavelet transform which was later combined with a time plane based method by Majumder et al [7]. Hayn et al [2] presented amongst others two template matching techniques. In the following, we present different algorithms for ECG feature extraction and describe their results and applications.

#### 3.1 Manual ECG feature extraction methods

A classical manual method for the QT interval measurement is the maximum slope intercept method: the tangent through the maximum down slope of the T wave is drawn. The T wave offset is then the intercept with the isoelectric line [12]. However, this method is too time-consuming for clinical practice. The visual observation of ECG patterns is widely used as well as ECG rulers.

#### 3.2 ECG Feature Extraction Based on Derivative-Threshold-Method

Hayn et al [2] developed an algorithm for the automated detection of peaks as well as on- and offset of the P and T wave and the QRS complex. The ECG signal is first split in single heart beats. The characteristic points of the ECG are then determined for each beat and each lead separately. In a second step the identified points of each lead are combined and one resulting on- and offset is calculated. For validation the Physionet QT Database, the CSE Multilead Database, and the PTB Diagnostic ECG Database were used.

QRS onset and T offset are required for the calculation of the QT interval whereof T offset is the more challenging part [2]. Both features are first detected coarsely. The coarse points are then used to determine the exact characteristic points.

First, the QRS onset is identified. For this purpose, a time window in which the QRS onset is expected is defined and applied to the filtered ECG signal. The ranges of the filtered signal amplitudes within the chosen interval are calculated and then compared with a threshold value. The first value that falls below the threshold value is chosen as the coarse QRS onset. By a repetition of this process with a stepwise decreased threshold-value and the calculation of the ratio between the mean range curve values right before and right after the particular onset point the exact QRS onset is identified as the point with the lowest ratio as described in [2].

The P and T wave peaks are determined analogously applying a time window on the signal and searching its extrema. For those a probability factor for being the P or T wave peak is calculated and the peaks with the highest factor are selected. The exact P and T on- and offsets are detected by means of a combination of the above mentioned threshold value method with a Gaussian approximation of the T wave. The latter defines the particular characteristic point (here the T wave offset) at the maximum of the Gauss curve plus 1.85 times its sigma value. Figure 4 illustrates the decreasing threshold-value method exemplified by the T wave offset determination as well as the Gaussian approximation (blue curve) of the T wave (black curve) and the associated T wave offset detection.

![Figure 4: Two methods for the exact T offset calculation: Left: decreasing thresholds for the range curve. Right: Gaussian approximation to the descending T wave [2]](image-url)

In a second step, the lead consolidation is performed. For this purpose, a confidentiality parameter which describes the credibleness of each point in each lead is introduced. The confidentiality parameters are then multiplied by the determined values. In case of two lead (as provided by the Physionet QT Database) the average value of these products is calculated to define the final characteristic points. In case of multilead recordings (CSE Multilead Database, PTB Diagnostic ECG Database) values that are smaller than 1/30 of the maximal value of all channels are ignored for averaging.

In a first version of the algorithm the median of the values from different leads is used for marking the ECG features whereas in the second version the earliest point is chosen for onset and the latest for offset. The algorithm reaches a sensitivity of 95% and obtained a score of 16.34 at the Computers in Cardiology Challenge in 2006 which was the highest score of all the participants.

It is notable that the first version of the algorithm is employed for ECG feature extraction although the second one constituted an improvement with respect to the exactness of the algorithm.
compared with the annotations of experts. On average, automated algorithms for QT interval measurement mark the QT offset significantly earlier than physicians do [4]. To reduce the deviations between the algorithm and the manual ECG analysis the latest point method was implemented. However, compared with other automated algorithms, the results showed significant deviations and errors. Furthermore, the median method is less exact indeed, but more stable and less susceptible to outliers. Both algorithms are suitable for the determination of changes in the QT interval duration which are of interest for example in clinical studies that investigate the influence of drugs on the electrical conduction of the heart.

Laguna et al [4] implemented another algorithm for automated location of characteristic points in the ECG as well as waveform boundaries based on a derivative threshold method. As a preparation for the detection of the ECG features, the ECG signal is filtered and differentiated.

The feature extraction consists of two main steps: the detection of characteristic points (QRS complex or rather R peak, P wave peak and T wave peak) and the determination of the waveform boundaries (on- and offsets). Using the estimates of the firstly executed single-lead QRS detection (a series of single-lead QRS locations is shown in Figure 5a) which are determined by an algorithm that is described elsewhere [4] a decision rule for the multilead QRS detection is applied to reject erroneous measurements. The earliest (min) and the latest (max) single-lead QRS location are identified and two 90ms time series are constructed: one starting at the min value and the other ending at the max value (see Figure 5b). The number of single-lead QRS locations in the series is counted and the min or the max value is rejected depending on which series contains the smaller number of QRS locations (Figure 5c). This process is recursively repeated until the two series are congruent (Figure 5d). The resulting interval is chosen as the final QRS location (Figure 5e).

The waveform boundaries for each lead are calculated on basis of the detected P and T peaks applying the derivative threshold method. The wave onset in single-lead is found as the backward crossing point of the differentiated wave with an applied threshold value whereas the wave offset is the forward crossing point.

To calculate the on- and offset of the multilead signal two time intervals are defined, the first beginning at the earliest onset respectively the second ending at the latest offset. If no more than two other leads have their onset (respectively their offset) within this interval the boundary is rejected as erroneous.

The method presented by Laguna et al was validated using the CSE multilead Database which allows the comparison of the new algorithm with previous ones tested by CSE as well as with human expert annotations. This comparison showed that the wave peaks and the wave boundaries were identified precisely and the calculated values showed only mean differences and standard deviations within the expert tolerance limits. Noticeably, the T offset was detected more precisely than by previous algorithms. Hence, a high agreement with expert annotations was reached.

The multilead ECG feature extraction permits the rejection of erroneous measurements by means of the comparison between the different leads.

3.3 ECG Feature Extraction Based on a Wavelet Transform

Mahmoodabadi et al [5,6] developed an ECG feature extraction system based on the multi-resolution wavelet transform using the Modified Lead II (MLII) for processing. They applied two different wavelet filters (Daubechies 4 and Daubechies 6) on ECG records from the MIT-BIH Database.

The wavelet transform is the convolution of a wavelet function ψ(t) with a signal x(t). Orthonormal dyadic discrete wavelets are associated with scaling functions φ(t) which can be used for the calculation of approximation coefficients S. S is the convolution of the signal with the scaling function. The further mathematical description is referenced in [5].

The application of the wavelet transform for the ECG feature extraction comprises the construction of an approximation signal by convoluting the signal with the wavelet function. This approximation function is used for the location of different ECG features and characteristic points. Applying the multi-resolution wavelet transform, the original signal is decomposed and the details for different scales at different locations of the signal are calculated. This decomposition permits the selection of suitable details for every characteristic point of the ECG signal which allows its precise approximation by making different features more noticeable. For ECG signals the Daubechies wavelet is beneficial because it matches closely the shape of the ECG signal.

The initial step of the feature extraction process is the removal of noise from the signal. Four algorithms for the different steps of extraction are implemented: First, the QRS complex or rather the R peak is detected. For this purpose, particular details of the transform are selected (in this case the details of scale 3 to scale 5). On this basis, the peaks of the Q and S waves are determined by searching the extrema to the left (Q wave peak) and the right (S wave peak) of the formerly detected R peak within an interval of 0.1 seconds.

In a next step, the zero-voltage level is identified by searching the Q wave onset point in the approximation signal keeping
details from scale 1 to scale 5. Shifts or alterations of the zero-voltage level can be determined by a comparison of the zero-crossings before the Q wave and after the S wave.

Finally, the P and T wave peaks are identified as the extrema before the first respectively after the second zero-crossing used for the zero-voltage level detection. The on- and offsets of the P and T waves are then the zero-crossings about P and T wave peaks (compare with Figure 3).

For the validation of the proposed method 46 multichannel long-term ECG records of the MIT DB Database were used. These records are annotated by human experts and for validation these annotations were compared with those produced by the algorithm. Moreover, the developed algorithm was tested in beat to beat processing where it gave acceptable results as well. [6]

Mahmoodabadi’s work showed that using the wavelet family Daubechies 6 gives better results than Daubechies 4. Most details about the original signal are reconstructed in lower scales where however, the influence of noise is higher. The developed system is the first in applying the algorithm in one run so that the whole signal samples are processed all at once taking into account all kind of beats. The developed QRS detector reaches a sensitivity of 99.18%±2.75 and a positive predictability of 98.00%±4.45.

3.4 Combination of the Wavelet Transform with a Time Plane Based Method

The main idea of Majumbder et al [7] was the combination of the wavelet based feature extraction as presented in [5,6] and the time plane based feature extraction which had the effect of reducing the average error in measuring the QT interval to less than 1%.

Analogously to the wavelet based method, there are four steps in the extraction procedure using the time plane based method. However, a fivpoint differentiation is applied to the original ECG signal and the waveform features are detected in the absolute differentiated wave. After the differentiation an interval which should be shorter than the time between two consecutive R peaks is chosen. The maximum point in this interval is defined and its polarity is tested. Depending on the algebraic sign the lowest point to the left or to the right to this maximum point is selected as the R point. Based on that R point, the Q point, S point as well as the T peak point and the T peak offset are determined as described more in detail in [7] looking for extrema in the differentiated wave.

After all, three different wavelets (db6, db8 and sym6) as well as the time plane based method were tested and evaluated using 530 recordings of the Physionet’s online QT challenge ECG database. The analysis of the records was conducted and evaluated separately for db6, db8, sym6 and the time plane based method and then the results of the different methods were compared. It was found that db6 gave the lowest average error (8.7483%) (see Figure 6). The time plane based method showed a negative average error (-7.157) with an absolute value approximately in the range of the db6 error. By averaging these two methods an average error of 0.96% was reached (see Figure 7). The Sym6 results were up to the mark except of some outliers that showed errors up to 50% (see Figure 6).

3.5 Fully Manual vs. Semi-automated ECG Feature Extraction Method

Hingorani et al [3] compared the fully manual with a semi-automated measurement of the QT interval using grouped and ungrouped superimposed median beats. They used a software program (Veritas; Mortara Instruments) which calculated a median beat from a ten second multilead ECG recording for each lead. The median beats for all leads were then monitored superimposed (superimposed median beat SMB) on a screen and automated annotations of the QT interval were made by a suitable automated measurement of the QT interval using grouped and ungrouped superimposed median beats. They used a software program (Veritas; Mortara Instruments) which calculated a median beat from a ten second multilead ECG recording for each lead. The median beats for all leads were then monitored superimposed (superimposed median beat SMB) on a screen and automated annotations of the QT interval were made by a suitable computer software application (CalECG version 2.1; AMPS LLC, New York, NY). These ECGs were then reread (the automated annotations were visible and could be moved in case of disagreement) by three trained ECG readers and later confirmed by board-certified cardiologists; one time with overlapping zero voltage levels of all median beats (grouped SMB) and a second time with a displacement of the zero voltage levels of the different leads for 5 to 10mm in vertical direction (ungrouped SMB). The ECGs originated from 38 test subjects randomly assigned to two groups with differing application of a QT prolonging drug (moxifloxacin) or a placebo. The detection of the resulting prolongation by the different methods (manual measurement, grouped SMB and ungrouped SMB) was investigated and compared.
It was shown that all the methods gave comparable results (only with minor deviations which were evaluated statistically) with respect to the assay sensitivity. That means that they all identified the QT intervals measured on ungrouped SMBs exceeded the values obtained from grouped SMBs in average of 4ms. Moreover, the ungrouped SMB values showed better agreement or rather minor errors compared with the automated annotations by the software application. Therefore, Hingorani et al suggest the implementation of ungrouped SMBs.

It is interesting to see that Hingorani et al [3] used a median beat in their study but not the original ten second ECG recording. This approach is discussed in section 4.

### 3.6 Conventional Extraction Technique vs. Template Matching Techniques

A study investigating the QT interval measurement and the ability of detecting QT variability using three different methods was performed by Baumert et al [1]. They compared the results obtained applying a conventional computerised QT measurement, a template stretching and a template time shifting method on simulated as well as real ECG before and after infusion of a QT prolonging drug.

The conventional computerised method is a derivative-based method which first detects the QRS complexes using a derivative-thresholding algorithm and then identifies the electrical baseline. Afterwards, the ECG curve is differentiated for a constant duration and the T wave on- and offset are determined by comparison with a threshold value. The obtained fiducial points are then validated or corrected by an expert cardiologist.

The main idea of the template stretching method is the manual evaluation of one beat via a graphical user-interface and appropriate markers. The algorithm then compares all the other beats with this template by testing how much a beat has to be stretched or compressed to best match the template. It calculates and minimises the matching error on the sum of squared differences calculating the optimum scaling factor.

The template time shifting method as a fully automated method is based on the construction of different templates for QRS and for the T wave and their time shift until they match a previously constructed template for the whole beat. The latter is obtained by the evaluation of a number of beats of the ECG signal and is purified every 60 beats to be responsive to changes in the ECG signal.

All three methods were tested on simulated ECG as well as on real ECG. For the simulated ECG a set of ten sequences with 500 cardiac cycles was constructed using the same beat but with a modulation of its T wave amplitude. Noise, baseline wander and amplitude modulation were simulated to evaluate the performance of the different algorithms under these conditions which are all linked with an artificial QT variability. The real ECG records originated from a study which included the infusion of a QT prolonging drug (sotalol) and served as a test for the ability of the three methods to identify QT variability.

The conventional method showed a major susceptibility to noise and the template time stretching method was sensitive for baseline wander. In contrast, the time shifting method was robust against these two but sensitive for amplitude modulation. None of the algorithms was able to detect a significant QT variability in real ECG after the infusion of sotalol. Furthermore, a significant inverse relationship between the T wave amplitude and the QT interval was observable which hinders the comparison of ECGs of different individuals or from different studies when the T amplitudes are not reported. Noticeable was the high rate of rejected beats of 17% when applying the template stretching method compared with 10% obtained by the time shifting method and 11% of manual corrected beats with the conventional method. Here, the latter has the advantage of providing a series with less missing beats because of the manual correction which can be beneficial for studying the temporal structure in the frequency domain. After all, Baumert et al however recommend the template time shifting algorithm given its higher overall flexibility, robustness against noise and independence from a particular operator.

### 4. SUMMARY AND DISCUSSION

Two of the presented methods are examples for derivative or threshold methods (see 3.2) whereas 3.3 describes ECG feature extraction based on a multi-resolution wavelet transform and a time plane based method is added in 3.4. In Section 3.5 a semi-automated extraction method is presented which employs the superimposed median beat. Moreover, two template based extraction methods are outlined (see 3.5).

The above mentioned wavelet transform method has the disadvantage that the detection of the characteristic points in the ECG is dependent on the firstly determined R peak because the latter is used for the calculation of all other values. The precise and exact R peak detection is therefore essential since an error affects all further points. Despite the influence of the R peak point, the multi-resolution wavelet transform and the decomposition of the signal allow a close approximation of the ECG signal given that for every single feature appropriate details can be selected which make noticeable one particular feature.

The comparison of the wavelet transform with the time plane based method showed that both methods give similar errors but with different algebraic sign: the wavelet transform marks the T wave offset too early while the time plane based offset is set to late. The resulting error is reduced by averaging the results of the two methods.

Until today, new developed algorithms are validated using ECG records from different databases and comparing the waveform features obtained from the algorithms with human expert annotations. Since these are not easily and reliably reproducible first attempts in searching an alternative were made and the fully manual feature extraction was compared with a semi-automated method applying the superimposed median beat [3] (see 3.5). The use of this averaged beat provides several advantages: the QT interval can be measured even if the end of the T wave is marred by an artifact or if there is a superimposed U wave in some leads or in case of a limb lead interchange during the recording of the ECG. Nevertheless, the changes in or rather the development of the QT durations and the shapes of the different beats and waves contain additional information which is beneficial for the ECG analysis.

An advantage of the manual ECG analysis is the supply of time series with less missing beats when compared with fully automated algorithms as described for the template based methods in [1] (see 3.6). The automated algorithms reject a significant number of critical beats which can be manually corrected applying the conventional method. In consequence, a larger number of beats is available for the feature extraction. The true benefit is however the additional information contained in the T wave shape which is of major importance for the medical
diagnosis. This information is lost when using fully automated algorithms or median beats.

The remaining discrepancy in the mark of the determined T wave offset between automated algorithms and expert annotations is exemplified in the two different existing versions for the algorithm developed by Baumert et al [2]. When they modified their algorithm to increase the agreement with the evaluation by physicians and therefore the performance of their algorithm, the reduction of agreement with other algorithms resulted. This ambiguity illustrates the need of further research on this regard.

5. CONCLUSIONS

Many different algorithms based on diverse methods have been developed for the automated ECG feature extraction. They are efficient and characterised by a high performance and show results that fulfill the requirements for sensitivity and error ranges satisfactorily. Today, automated ECG feature extraction algorithms are standard in clinical practice and support physicians in the evaluation of ECG curves and medical diagnosis. A significant factor in this context is the saving of time which becomes more important in consideration of current changes in health care systems. Another advantage of automated algorithms is the elimination of operator-dependence which makes measurements more reproducible.

Nevertheless, the precise detection of ECG features is still not resolved or completed. The development of an algorithm that is able to take into account the amount of information contained in the ECG waveform is meaningful but challenging. The extensive ability of humans in pattern recognition and matching cannot be reproduced by a computer so far. Moreover, the ECG shapes show a wide variability because the anatomy, physiology and functionality of the heart are different from human to human. Patterns differing to a great extend can still be physiological instead of indicating an underlying heart disease.

Still, there is no gold-standard or algorithm that would give precise and always reliable results as illustrated in the study carried out by Baunert et al [1] where it turned out that none of the tested algorithms was able to detect a QT variability after the infusion of a QT prolonging drug. Moreover, these results pointed out the requirement of a high qualitative, noise free ECG recording because noise affects the performance of extraction algorithms. Especially for the QT duration the clear detection of the T wave offset which is however often masked by noise is crucial because a prolongation of only a few milliseconds (in an interval of a total length of up to 500ms or more) can indicate a cardiac disorder. This fact points out the requirement of precise and exact measurements.

6. FUTURE WORK

The remaining discrepancy in the mark of the T wave offset requires further investigation. Furthermore, the development of algorithms that take into account the T wave morphology would be beneficial given that the T wave morphology contains much vital information which could permit an improved medical diagnosis.

7. REFERENCES


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