PILOTING REAL-TIME QRS DETECTION ALGORITHMS IN VARIABLE CONTEXTS

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Abstract: This paper presents a cardiac arrhythmia medical monitoring system that can modify and change the components of its processing chain to carry out the best treatment on electrocardiogram (ECG) signal. The most important feature to detect in the ECG is the QRS complex. However, the experience gathered over several years, shows that the proposed strategies to detect the QRS complex have reached an asymptotic detection performance. We propose to use a mixture of low-level and high-level information, called the current context, to pilot QRS detection algorithms in order to reduce the number of errors. The algorithms are piloted according to a set of piloting rules acquired by statistical analysis. Results of piloting three QRS detectors on five test ECGs corrupted by real clinical noise, show that the pilot enables to reduce the error rate from 14,3% to 10,6%. These results are useful to the development of a real-time monitoring system which can choose the best algorithm to recognize arrhythmias in clinical noisy context. The presented approach is not restricted to the QRS complex detection but can be extended to the processing of other biomedical signals.

Introduction

In medical monitoring, the reduction of false alarms and missed detections is a major objective. Medical monitoring systems, such as CALICOT [1], are generally composed of two distinct parts: a *temporal abstraction* part, dedicated to the acquisition, the processing and the analysis of the signal, and a *medical diagnosis* part which computes a diagnosis from the data transmitted by the temporal abstraction and from a knowledge base. When a change appears in the input data, the temporal abstraction must react to adapt it-self to the new context. Otherwise, the temporal abstraction transmits erroneous data and causes false alarms and low quality diagnosis. It is thus important to select carefully the signal processing algorithm best suited to the current context. Moreover, the diagnosis part itself does not always need information with the same level of detail. It can be costly in terms of quality results to be too much demanding when it is not needed. It is thus also important to tune the temporal abstraction task according to the current diagnosis hypotheses. Our objective is to improve the cardiac monitoring system CALICOT by adding a pilot which choose, according to the context, the best algorithms to extract features from the electrocardiographic signal (ECG).

In automatic ECG analysis the most relevant tasks is the detection and characterization of every wave, particularly of the QRS complex, after which a more complete analysis can be obtained [2, 1]. Therefore, choosing the QRS detection algorithm is an essential step in the development of a real-time ECG analysis system. Experience gathered over several years, shows that the proposed strategies for ECG analysis and particularly for QRS complex detection based on signal processing techniques, have reached an asymptotic detection performance. This is mainly due to the multiplicity of situations met in clinical environments. An alternative is to use the best detection algorithm, according to the current context. A pilot which choose the QRS detector in real time according to the situation can accomplish this task.

Many QRS detection schemes are described in the literature [3, 4, 5, 6, 7] and are still being proposed [8, 9]. To quantitatively compare them, the classical approach [6, 7] is to compute, over a set of different ECG records, an average score expressed as sensitivity-specificity pair that is assumed to reflect the overall performance of the detectors. A limitation of this method is that an ECG is composed of multiple noise levels and types, and a variety of beat morphologies. As reported in [10], an average score hides the problems that are still present in case of noisy or pathological signals because it does not explain what are the specific ECG contexts that affect the detection. In our study, a context is defined as a particular combination of noise and QRS morphologies. A change of the noise energy or a change of the QRS morphology within an ECG record implies a change of context.

To assess the specific contexts that influence the QRS detector performance, a statistical analysis was done in [11]. Results showed that no QRS detector can achieve the QRS detection task better than other detectors in all contexts. This communication continues this study by interpreting the results and implementing a pilot in the cardiac monitoring system CALICOT. In section 1, the monitoring system CALICOT is briefly described. The section 2, presents the different ways to pilot CALICOT, the new architecture and the pilot module. The acquisition of the

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QRS piloting rules is explained in section 3. In the Result section, the acquired QRS piloting rules and results obtained by piloting QRS detection algorithms are analyzed. A discussion and a short conclusion end the paper.

Materials and Methods

1 The Calicot monitoring system

Calicot [1] is a monitoring system devoted to cardiac arrhythmia recognition. Arrhythmias are heart diseases related to heart contraction dysfunctions. Heart contractions are ensured by an electric stimulus which goes through the four heart rooms: the two atria chambers and the two ventricles. Any disturbance in the course of this stimulus is called an arrhythmia. The electrocardiogram (ECG) is used in clinical routine to obtain an image of the propagation of the electrical signal inside the heart. The main waves of the ECG signal are the P wave and the QRS complex. They correspond respectively to the depolarization of the atrias and the ventricles which induces the contraction of these chambers. An arrhythmia can be diagnosed from the morphology of the P and QRS waves and their temporal relationships.

Calicot computes a diagnosis from an abstracted ECG representation. This system is composed of two on-line main modules (see Figure 1 1): a temporal abstraction module and a chronicle recognition module. A chronicle [12] is a temporally constrained pattern which is characteristic of an arrhythmia. It is described by a set of events (in our case, P waves and QRSs) interlinked by time constraints. These chronicles are learned (off-line) by an inductive logical programming method. Starting from annotated ECG examples related to an arrhythmia, the learning system produces recognition rules which are translated into chronicle models.

The temporal abstraction is achieved by signal processing (SP) algorithms that detect and classify the ECG events (QRS complex or P wave) from the ECG signal. The chronicle recognition module analyzes the events flow and computes the diagnosis by searching for signal chunks matching the chronicle models.

Calicot demonstrated satisfactory performances [1]. However, it remains sensitive to the temporal abstraction errors which can cause diagnosis errors. A pilot that selects, according to the signal and diagnosis context, the best adapted SP algorithm appears then as a smart alternative.

2 The new architecture

Calicot is improved by piloting its processing chain according to the current context. Algorithm piloting derives from various works, especially from the notion of *program supervision* [13] which represents a signal processing task by a plan of primitive operations. Other works [14] proposed an architecture for on line self-adaptive software. In the medical monitoring domain and more specifically in the QRS detection, a cardiac monitoring system was proposed which uses two QRS detection algorithms that switch when the situation is most adapted to one of the detector [15]. Our approach is an adaptation of the previous works but takes into account the arrhythmia monitoring specificity and the need to change dynamically the abstraction reasoning of the signal interpretation.

2.1 Three ways to pilot Calicot

Calicot is piloted in three ways. The pilot activates and deactivates temporal abstraction tasks, chooses and tunes SP algorithms, and selects the level of detail that the arrhythmia recognition needs. The bottom of Figure 1 gives the architecture of the new system with the pilot.

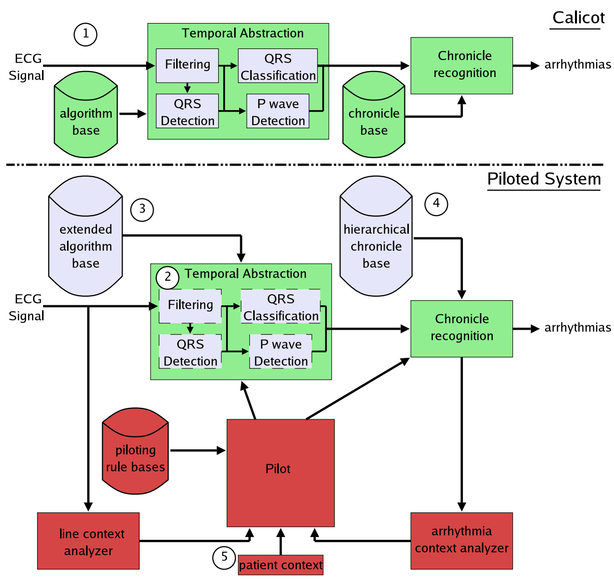

Figure 1: General architecture of the system. The top chain represents Calicot modules and the bottom chain represents the modules added to Calicot to pilot it.

2.1.1 Arrhythmia recognition piloting

An arrhythmia can be diagnosed according to several ECG features. In Calicot, all the features are constantly extracted and sent to the arrhythmia recognition, but in some contexts, a reduced number of features can be sufficient to recognize an arrhythmia. For example, in the presence of a fast heartbeat rate, one can be in presence of a ventricular tachycardia or a supra-ventricular tachycardia. Arrhythmia recognition based on P waves can discriminate them. But, the analysis of the QRS morphology, which is less time-consuming and more robust than the P wave analysis, is sufficient to discriminate the two arrhythmias. Thus, the arrhythmia recognition piloting consists in choosing the abstraction level of the chronicles to recognize by selecting the corresponding chronicle models, according to the current diagnosis hypothe-

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ses. To represent these various abstraction levels, a hierarchy of chronicle models (i.e. arrhythmia models) are learned from a set of examples expressed in the four following languages:

L1 includes the QRS occurrence date plus the temporal interval between QRS occurrence;
L2 adds to L1 the QRS morphology;
L3 adds to L1 the P wave occurrence date;
L4 adds to L2 the P wave occurrence date.

The four levels of chronicle models *C1, C2, C3 and C4* constitute the hierarchical chronicle base 4. For example, if the P wave is not needed then the chronicle base *C2* is chosen. In all cases, the QRS detection is activated. This implies a great need of a QRS detection which performs without errors even in presence of noise.

2.1.2 Temporal abstraction piloting

The temporal abstraction is composed of four linked tasks which extract three main features:

Filtering separates the actual ECG signal from the noisy part of the signal;
QRSDetection identifies QRS occurrence dates;
QRSClassification labels QRS morphologies;
PWaveDetection identifies P wave occurrence dates.

In CALICOT 1, each task is always activated. But, if a chronicle base such as *C2* is chosen, then the *PWaveDetection* task must be deactivated because it is not needed for arrhythmia recognition. Moreover, in several circumstances, some tasks cannot be achieved. For example, if the line is too noisy to accomplish the P wave detection without errors then *PWaveDetection* task must be deactivated. If not, this task penalizes the whole system because it provides false information to the chronicle recognition module. To be more efficient and to base the recognition on reliable information, the new architecture enables the activation and deactivation of the temporal abstraction tasks 2 according to the needs and to specific contexts.

2.1.3 SP Algorithms piloting

The temporal abstraction tasks are performed by SP algorithms. In CALICOT, a unique SP algorithm is devoted to a particular task. However, in the literature, there exist several possible algorithms to achieved these tasks whose performances vary according to the context. The preliminary study, described in [11], showed that the performances of various QRS detection algorithms change with the current context (line noise and QRS morphology). The new extended algorithm base 3 contains several SP algorithms for each task. Thus, the role of the pilot is to choose the best suited algorithm according to the current context and then, to tune its parameters.

The three piloting levels interact in order to have consistent decisions. For example, a type of chronicle models cannot be selected if the corresponding needed tasks cannot be activated.

2.2 The context and its analysis

The context 5 is composed of three sub-contexts: line context, arrhythmia context, and patient context. The patient context (age, basic ECG rhythm, etc.) is static whereas the line context and the arrhythmia context are dynamic and are regularly updated by the two analyzers.

The *line context* describes the level and the type of noise on the line. We consider three types of noise encountered in real clinical situations: the *baseline wander* (*bw*), which is mainly low frequency; the *muscle artifact* (*ma*), which is mainly high frequency; and the *electrode motion artifact* (*em*), which has components at high and low frequencies. The line context analyzer is connected directly to the input line, which enables a quick communication of the line context to the pilot. Thus the temporal abstraction is modified before the ECG processing.

The *arrhythmia context* analyzer uses the chronicle recognition assumptions to make a list of the arrhythmias that are most likely to appear. This list is the arrhythmia context. From this arrhythmia context, the pilot can deduce the main ECG waveforms that the temporal abstraction have to extract. For example, from the current arrhythmia context, expert rules infer the main QRS waveforms, which are symbolized by the letters: *N* (normal), *A* (Atrial premature beat), *J* (Jonctional premature beat), *V* (Premature ventricular contraction), *F* (Fusion of ventricular and normal), *P* (Paced beat), *R* and *L* (Right and Left bundle branch block beat).

2.3 The pilot

The architecture of the pilot is depicted by Figure 2. It is composed of three inference engines which deduce the actions to perform on the system for the three piloting levels and a context manager which deduces the information needed by the engines from the current context.

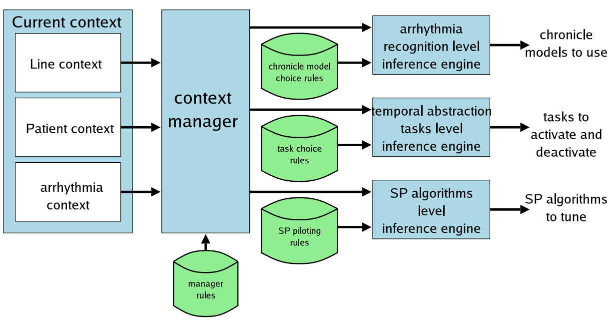

Figure 2: The pilot architecture.

The role of the context manager is to instantiate and update useful variables from the raw information transmitted by the context analyzers. For example, *tooMuchNoiseForPWave* is true only if the line is corrupted. Similarly, from the arrhythmia context, the context manager deduces the main QRS waveforms that will be processed by the temporal abstraction. In this sense, the context manager updates the fact base as in a classical expert system. Its knowledge is represented by expert rules stored as rules of thumbs in *the manager rule base*.

The system is piloted at three levels: the arrhythmia recognition level, the temporal abstraction tasks level, and the SP algorithms level. From the information transmitted by the context manager, the engines infer the actions to perform on the system. Their piloting rules are mainly defined by an expert and are grouped into: chronicle model choice rules, task choice rules, and SP algorithm choice rules. The chronicle recognition adapts the abstraction level to the context. For example, if only the QRS occurrence date and QRS morphology are needed and technically achievable, then the chronicle recognizer must use the definition *C2*. The temporal abstraction tasks are activated according to the needs and to technical constraints. For example, to activate *PWaveDetection*, it is necessary to have a non disturbed line. The SP algorithm choice rules determine the best suited algorithm according to the temporal abstraction tasks and tune it. For example, if the *QRSDetection* task is active, then it is necessary to choose the most suitable detector.

3 Acquisition of the QRS detection piloting rules

To acquire the piloting rules of the QRS detectors, a statistical analysis was done in [11]. Succinctly, the method consist in generating a large ECG database relevant to clinical situations. These ECGs contain different combinations of QRS morphologies and clinical noise and are used to test QRS detectors. The detector scores (detailed below) are then compared by means of a multivariate analysis. The test procedure is described Table 1.

Table 1: Resampling (pseudo-bootstrap) algorithm to compute score of QRS detectors

Init.	Experiment: For a given context, suppose a set Q of BT beats of K samples
Step 1	Resampling: Draw a random selection of B beats, with replacement, from Q to obtain the resampled population Q^*
Step 2	Linking: Concatenate the B beats of Q^* using a sigmoid function on several samples so as to minimize the baseline shift between two adjacent beat segments
Step 3	Addition of noise: Corrupt the concatenated beats by real additive noise at a specific Signal-to-Noise Ratio to obtain S. For the generation of uncorrupted morphology contexts, step 3 is ignored
Step 4	Filtering: Filter S to obtain the signal S'
Step 5	Calculation of the score: Use S' as input of each one of the detectors and compute the score
Step 6	Repetition: Repeat steps 1 to 5 to obtain R realizations of the same context
Step 7	Repetition: Repeat the algorithm for each given context to collect all the scores
Step 8	Presentation of the results: Project all the scores on principal axes (PCA) to visually analyze their dispersion

In a previous study [11], the set of contextual ECG corresponding to the 8 QRS morphologies (*cf.* 2.2), has been extracted from 17 standard ECG records of the MIT-BIH Arrhythmia database[1]. For each morphology, the set of extracted beats, ranging from 30 to 23000, are resampled to generate 50 realizations of 20 concatenated beats. These realizations are then used as input to the QRS detectors, without noise, and with 3 different types of additive clinical noise (*cf.* 2.2) extracted from a noise stress test database [16] at 3 signal-to-noise ratios (5, -5, -15dB). Four real-time QRS detectors were used:

pan : the Pan and Tompkins [3];
gritzali : the Gritzali's detector [4];
$df2$: the Okada's detector modified by [5];
$af2$: a derivative QRS detector modified by [5].

Performance is assessed by the number of errors (Ne), which reflects both false alarms and missed beats. For each test, FN (the number of False Negatives – missed QRSs) and FP (False Positives – false alarms) are computed to obtain $Ne = FP + FN$. The Error rate is $Er = \frac{Ne}{N_{QRS}}$ where N_{QRS} is the total number of actual QRSs. The study leads to 16000 Ne values, for such an amount of data, a Principal Components Analysis (PCA) was performed to analyze graphically the detector results.

Results

QRS detectors piloting rules

PCA analysis enables to emphasize situations in which one detector performs better than others. Figure 3 presents the projection of the detectors scores on PCA axes for ECGs corrupted with *em* noise.

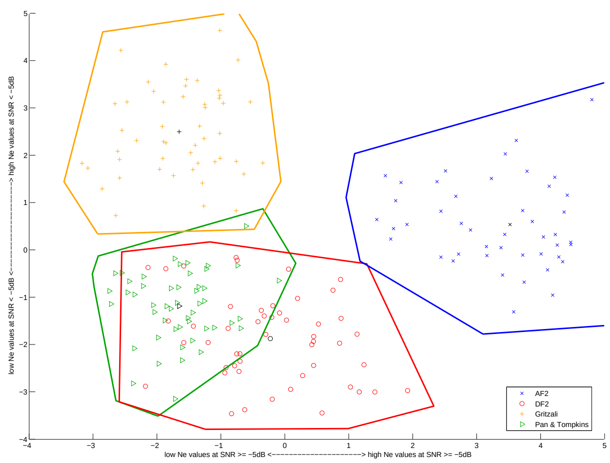

Figure 3: Principal Components Analysis on ECG contexts corrupted with electrode motion artifact.

The first axis presents a positive correlation with Ne values of signal contexts that have $SNR \geq -5dB$. The sec-

[1] http://ecg.mit.edu/

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ond axis presents a positive correlation with Ne values of noisy signal contexts ($SNR < -5dB$). This figure shows that *pan* and $df2$ are more able to perform a QRS detection in case of *em* noise than *gritzali* and $af2$. From PCA results, following piloting rules were inferred:

IF <*L* **and** *bw* **and** $SNR \geq -5dB$>
THEN <*choose Gritzali's QRS detector*>

IF <(*L* **or** *F*) **and** *no_noise*>
THEN <*choose Gritzali's QRS detector*>

IF <(*F* **or** *P*) **and** *bw* **and** $SNR \geq 0dB$>
THEN <*choose Gritzali's QRS detector*>

IF <*em* **and** ((*N* **or** *A* **or** *P* **or** *R*) **and** $SNR = -15dB$)>
THEN <*choose df2 QRS detector*>

IF <*em* **and** ($SNR = -5dB$ **and** *P*)>
THEN <*choose df2 QRS detector*>

IF <*default*>
THEN <*choose Pan's QRS detector*>

The first rule says that if the line context has the value *bw noise at -5 dB* and the arrhythmia context informs that it has mainly QRS of form L, then the gritzali's detector is chosen.

QRS detection results

To test the piloting rules, five ECGs were generated from the MIT-BIH database. Each ECG lasted from 20 to 30 minutes and about 2 hours in all. Three to four different contexts are introduced in each test ECG to assess the system performances in the specific contexts as well as around the context transitions. Parts of the original ECGs were corrupted with the three real clinical noise types defined before (*bw*, *ma*, *em*).

In each context, the pilot chooses the most adapted algorithm with the aid of the piloting rules. In this study, the algorithm thresholds are optimal in the sense that *Ne* is minimum.

Table 2: Results of the QRS detection task with different detectors and with the pilot (***** algorithms chosen by the pilot)

ECG	**1**	**2**	**3**	**4**	**5**	**Total**	
score	*Ne*	*Ne*	*Ne*	*Ne*	*Ne*	*Ne*	*Er*(%)
pan	***20**	***91**	*240	*312	*367	**1030**	**14,3**
gritzali	**20**	*160	388	360	***295**	1223	17
$df2$	307	278	***174**	***160**	*302	1221	17
pilot	**20**	**88**	**185**	**167**	**304**	**764**	**10,6**

The results of Table 2 show that the best algorithm is different in each ECG context. In the first case, *pan* and *gritzali* are the best for all the contexts, however according to the piloting rules only *pan* is used by the pilot. For ECG 2 (*cf.* Figure 4), *pan* is the most robust to *ma* noise whereas *gritzali* and $df2$ are highly disrupted. In the *bw* context, *gritzali* exhibits better performances than *pan*. That is why the pilot, by using both *pan* and *gritzali*, has the best results. In a similar way, the pilot uses *pan* and $df2$ for ECG 3 and ECG 4 which exhibit *em* context. In these cases, the pilot exhibits results close to those of

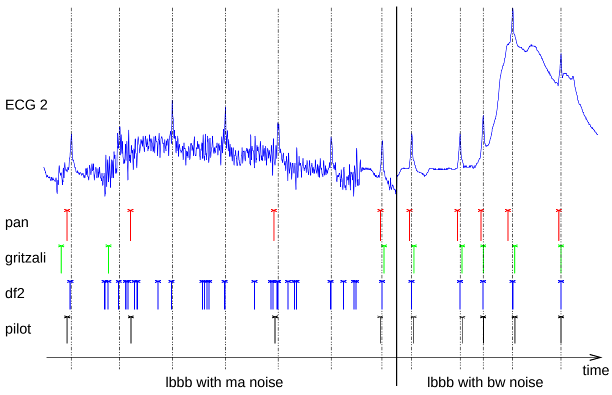

Figure 4: Context transition of ECG 2 with QRS occurrences for each detector. Dotted lines are actual occurrences of QRS.

$df2$, the best detector. This difference is due to the way the ECG is processed. In real-time processing, the signal is acquired by buffer. After filtering, the buffer is processed by the selected QRS detector. But, a buffer which contained two different contexts (context transition) is processed by only one QRS detector. For example, in ECG 3, the transition between the first context without noise and the second context with *em* noise is contained in one buffer and the pilot has selected *pan* (because of the first context) whereas $df2$ is a better choice.less errors than the pilot.

The pilot obtains always a score very close to the best detector because it benefits, in each context, from the best algorithm performances. But, because of the nature of the piloting rules, the pilot may not have the best results. Actually, the rules express a general tendency (statistical tendency) and not an absolute behavior. For example, $df2$ is the best in *em* context but sometimes *pan* can be as good as or better than $df2$ (see Figure 3). However, a smart management of the input signal, as an adaptation of the buffer length to the context length, could improve the pilot results.

Even if the pilot is not always the best in every contexts, the total scores show that the pilot makes globally less errors than the best detector (*pan* here). This demonstrates the value of using a smart piloting of QRS detection algorithms according to a mixture of signal processing domain information (line noise context) and medical information (arrhythmia and patient context), to improve the QRS detection complex which is the most important wave in ECG analysis.

Discussion

We have proposed an approach for taking the context into account during signal processing. We propose to choose and adjust the most adapted SP algorithm according to a mixture of low level information (line context) and high-level information (arrhythmia and patient context). Intelligent monitoring systems are generally composed of a low-level part (temporal abstraction) related to the signal processing domain, and a high-level part (arrhythmia recognition) more related to the artificial intelligent domain. However, few IA reasoning system take into account the errors generated by the low level stage, assuming that it is only a specific signal processing problem. In the field of signal processing, improvements have been done to include some kind of reasoning into the algorithms. For example, a rule such as *if nothing is detected during a certain time then decrease the threshold* can be used [3]. But, these solutions, even if they improve the SP algorithms, take only the local information into account and not high level reasoning results as current recognized arrhythmias. In our study, the QRS detector performance have been studied according to the QRS morphology and the clinical noise. The results show that this kind of knowledge is useful to improve the QRS detection stage in a cardiac monitor. However, an other important feature to explore is the transition between two different QRS morphologies. For example, in arrhythmia context, the QRS morphologies vary rapidly between consecutive beats. An other study has been done (not presented here) with different arrhythmias (normal, tachycardia, bigeminy, trigeminy, mobitz, etc.) to assess the QRS detector performances with transitions of QRS morphologies. Results are very similar than those obtained with no transition. For example, results obtained with tachycardia, bigeminy and trigeminy are very close to those obtained with V morphology alone.

Even if the results are limited to simple algorithms, the method is general and other detectors such as those recently proposed [7, 8, 9], are going to be integrated to the algorithms base.

Conclusions

This work shows that an improved QRS detection performance can be obtained by selecting the most appropriate algorithm for a given context. Using this kind of knowledge – the current context –, the average error rate of 14.3% obtained with the best QRS detection algorithm fell to 10.6% when a pilot was used. The proposed approach is general and not restricted to the QRS complex detection. The detection of other ECG waves (P waves) or other biomedical signals waves such as spikes in EEG can be enhanced using an algorithms pilot.

The results of piloting QRS detection algorithms are very encouraging and ongoing work is focused on piloting the arrhythmia recognition and the temporal abstraction tasks. This piloting will ensure a more efficient arrhythmia recognition which uses always the reliable information for a robust medical diagnosis even in a noisy context.

References

[1] CARRAULT, G., CORDIER, M.-O., QUINIOU, R., and WANG, F. Temporal abstraction and inductive logic programming for arrhyhtmia recognition from electrocardiograms. *Artif. Intell. Med.*, 28:231–263, 2003.

[2] VILA, J., PRESEDO, J., DELGADO, M., BARRO, S., RUIZ, R., and PALACIOS, F. Sutil: Intelligent ischemia monitoring system. *Int. J. Med. Inform.*, 47:193–214, 1997.

[3] PAN, J. and TOMPKINS, W.J. A real-time QRS detection algorithm. *IEEE Trans. Biomed. Eng*, 32(3):230–236, 1985.

[4] GRITZALI, F. Towards a generalized scheme for QRS detection in ECG waveforms. *Signal Process.*, 15:183–192, 1988.

[5] FRIESEN, G.M., JANNETT, T.C., JADALLAH, M.A., YATES, S.L., QUINT, S.R., and NAGLE, H.T. A comparison of the noise sensitivity of nine QRS detection algorithms. *IEEE Trans. Biomed. Eng*, 37:85–98, 1990.

[6] KADAMBE, S., MURRAY, R., and BOUDREAUX-BARTELS, F. Wavelet transform-based QRS complex detector. *IEEE Trans. Biomed. Eng*, 47(7):838–848, 1999.

[7] BENITEZ, D., GAYDECKI, P.A., ZAIDI, A., and FITZPATRICK, A.P. The use of the Hilbert transform in ECG signal analysis. *Comput. Biol. Med.*, 31:399–406, 2001.

[8] BURKE, M. and NASOR, M. Wavelet based analysis and characterization of the ECG signal. *J. Med. Eng. Technol.*, 28(2):47–55, 2004.

[9] DOTSINSKY, I.A. and STOYANOV, T.V. Ventricular beat detection in single channel electrocardiograms. *Biomed. Eng. Online*, 3(1), 2004.

[10] KOHLER, B.-U., HENNIG, C., and ORGLMEISTER, R. The principles of software QRS detection. *IEEE Eng. Med. Biol. Mag.*, 21(1):42–57, 2002.

[11] PORTET, F., HERNÁNDEZ, A.I., and CARRAULT, G. Evaluation of real-time QRS detection algorithms in variable contexts. *Med. Biol. Eng. Comput.*, 43(3):381–387, 2005.

[12] CORDIER, M.-O. and DOUSSON, C. Alarm driven monitoring based on chronicles. In *SAFEPROCESS 2000*, pages 286–291, Budapest, Hungary, 2000.

[13] SHEKHAR, C., MOISAN, S., and THONNAT, M. Towards an intelligent problem-solving environment for signal processing. *Math. Comput. Simul.*, 36:347–359, 1994.

[14] KARSAI, G. and SZTIPANOVITS, J. A model-based approach to self-adaptive software. *IEEE Intell. Syst.*, 14:46–53, 1999.

[15] SOULAS, T., LE CERTEN, G., LE PICHON, J.P., and CARRAULT, G. Algorithm switching in real time monitoring. In *Symposium on Electronics and Telecommunications (ETC)*, pages 145–149, Timisoara, 1998.

[16] MOODY, G.B., MULDROW, W.E., and MARK, R.G. A noise stress test for arrhythmia detectors. *Comput. Cardiol.*, 11:381–384, 1984.

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