Maejo Int. J. Sci. Technol. **2016**, *10*(02), 127-141; doi: 10.14456/mijst.2016.12

Maejo International Journal of Science and Technology

ISSN 1905-7873
Available online at www.mijst.mju.ac.th

Full Paper

Automatic electrocardiogram signal quality assessment in continuous wireless monitoring

Tanatorn Tanantong [1,*], Ekawit Nantajeewarawat [2] and Surapa Thiemjarus [3]

[1] Medical Informatics Department, College of Information and Communication Technology, Rangsit University, Pathum Thani 12000, Thailand
[2] School of Information, Computer and Communication Technology, Sirindhorn International Institute of Technology, Thammasat University, Pathum Thani 12000, Thailand
[3] National Electronics and Computer Technology Centre, Pathum Thani 12120, Thailand
* Corresponding author, e-mail: tanatorn.t@rsu.ac.th

Received: 25 October 2015 / Accepted: 13 April 2016 / Published: 16 May 2016

Abstract: This paper presents an automatic signal quality assessment method for continuously monitoring electrocardiogram (ECG) signals using wireless sensors attached to human bodies, with particular attention being given to ECG signals captured while the subjects are performing daily routine activities. In this study signal recordings from three databases are used: two ECG databases acquired using wireless body sensor networks from young subjects and elderly subjects during their daily routine activities, and the Massachusetts Institute of Technology - Boston's Beth Israel Hospital arrhythmia database. From these databases, ECG signals are divided into small segments, each 5 seconds long, and are then labelled with two levels of quality, i.e. 'low-quality' and 'high-quality'. For feature extraction, two levels of statistical features are employed: (i) window-based temporal features and (ii) segment-based features. The latter are derived from statistical values of the window-based temporal features and ECG signal amplitudes. A correlation-based feature selection algorithm is applied to find an optimal set of features. For signal quality classification, four machine-learning-based classification algorithms, i.e. Instance-based Learning, Decision Tree, Multilayer Perceptron and Rule Induction, are compared.

Keywords: wireless sensor networks, home health monitoring, ECG quality assessment

---

Maejo Int. J. Sci. Technol. **2016**, *10*(02), 127-141; doi: 10.14456/mijst.2016.12

INTRODUCTION

Continuous health monitoring systems using wireless wearable sensors have drawn much attention from the research community [1-3]. By monitoring the patient's vital signs, e.g. oxygen saturation, respiration rate, blood pressure rate, heart rate and body temperature, the feedback concerning the current health status can be provided in real time to the medical profession for making a suitable diagnosis. A continuous monitoring system can be applied to a wide range of medical applications for both the patient treatment and prevention, e.g. monitoring cardiovascular disease (CVD) patients [1, 2], monitoring patients during physical rehabilitation after surgery [3], and detecting emergency situations such as falls in an elderly person [4]. According to a report published by the World Health Organisation [5], CVDs have been one of the major causes of non-communicable diseases (NCDs): 17.5 million deaths were due to CVDs in 2012, representing 46% of all NCD mortalities. Of this number, 7.4 million and 6.7 million were caused by heart attacks and strokes respectively. In order to prevent sudden cardiac deaths, continuous electrocardiogram (ECG) monitoring is needed for early detection of the patients' abnormalities. Some studies [6-8] have recently presented continuous ECG monitoring systems using wireless sensors, which can probably be used for monitoring patients at home.

In continuous cardiac monitoring, ECG signals are easily contaminated by noises and artefacts, e.g. baseline drift and motion artefacts [9], which results in low-quality signals and leads to a high rate of false alarms [10]. Several studies have presented methods for automatic ECG signal quality assessment. Chudacek et al. [11] proposed a rule-based system for detecting common types of noises in ECG signals, e.g. baseline drift, power line interference and motion artefacts. Based on statistical values of ECG signal amplitudes, five noise-detection rules were used for classifying low-quality signals. Kuzilek et al. [12] developed a three-step method for ECG signal quality assessment. First, a threshold-based rule constructed from statistical values of signal amplitudes was used to determine the quality score of each signal recording. Secondly, the quality score of each signal recording was independently determined using Support Vector Machine, with features including kurtosis values, covariance matrices and time-lagged covariance matrices. The quality scores obtained from these two steps were next combined and used for deciding whether a signal recording should be accepted. Zaunseder et al. [13] proposed a method for assessing the ECG signal quality based on Ensembles of Decision Trees (EDTs) created by bootstrap aggregating. ECG features related to signal frequency contents, e.g. power in the high frequency noise (45-250 Hz) and low frequency noise (0-0.5 Hz), were used for constructing EDTs. Johannesen et al. [14] presented a two-step algorithm for assessing the quality of ECG signals. Signal recordings with lead connection issues, i.e. signal absence and large voltage saturation, were first excluded. Next, three different quality scores, ranging from 0 to 10, were determined for each signal recording based on the type of ECG noises, i.e. baseline drift, power line interference and muscular noises. Using these quality scores, a rule set was employed to determine whether the signal recordings were acceptable. In all the above work [11-14], ECG signal recordings were obtained from Physionet Challenge 2011 database [15], which contained signal recordings (each 10 seconds long) acquired from normal subjects using mobile devices. Further experiments on ECG signals captured while a subject is performing daily routine activities and on arrhythmic ECG signals are required.

In this study we propose a machine-learning-based method for automatic signal quality assessment in continuous wireless monitoring. To develop and validate the method, ECG signal recordings from three databases were used. ECG signals in the first and second databases were

Maejo Int. J. Sci. Technol. **2016**, *10*(02), 127-141; doi: 10.14456/mijst.2016.12

acquired from young subjects and elderly subjects respectively, using wireless Body Sensor Networks (BSNs) attached to the human bodies. The young subjects and the elderly subjects were asked to perform sixteen and seven daily routine activities respectively. The third database was obtained from the arrhythmia database of Massachusetts Institute of Technology - Boston's Beth Israel Hospital (MIT-BIH) public standard. To label ECG signals with quality levels, signals in these databases were discomposed into 5-second segments. Two levels of statistical features were extracted from the obtained signal segments. In the first level, window-based temporal features were extracted from statistical values, e.g. mean, variance and slope of each 1-second sliding window. In the second level, segment-based features were derived from statistical values of the window-based temporal features and those of ECG signal amplitudes. In order to select an appropriate set of features, a correlation-based feature selection algorithm was applied to the segment-based features. Four machine-learning-based classification algorithms, i.e. Instance-Based Learning (IB*k*), Decision Tree (J48), Multilayer Perceptron (MLP) and Rule Induction (PART), were used for constructing signal-quality classification models from the first database, and the best obtained classifier was tested on the other two databases.

MATERIALS AND METHODS

Data Description

Lead-II ECG signal recordings from three databases were used. The first and second databases, DB_1 and DB_2, were used for investigating the effects of the use of wireless-portable devices to capture signals from human subjects in free-living environments. The third database, DB_3, was employed to investigate the performance of a signal quality assessment model for ECG signals captured from subjects with heart diseases. In most studies on continuous monitoring using wireless devices [16-20], the number of human subjects used for framework evaluation was in the range of 5-27 subjects. For example, 5 subjects were used for evaluation of fall detection using acceleration and gyroscope signals [16], 12 subjects for evaluation of signal quality classification using ECG signals [17], and 20 subjects for evaluation of activity recognition using physiological signals [18]. For activity recognition using ECG signals [19, 20], 23 and 27 subjects were used for evaluation. In this study signal recordings for DB_1 and DB_2 were captured from a total of 20 subjects through wireless devices.

DB_1 comprises ECG recordings acquired from 10 healthy young volunteer subjects (3 females and 7 males) aged between 27-44 years at Thammasat University. DB_2 comprises ECG recordings acquired from 10 healthy elderly volunteer subjects (8 females and 2 males) aged between 57-71 years at Charoenkrung Pracharak Hospital. ECG recordings in both DB_1 and DB_2 were acquired at 100 Hz with 12-bit resolution using a wireless BSN node [21] attached to the subject bodies. None of the subjects had a clinical record of heart disease.

In order to incorporate noises arising from body movements, ECG signals in DB_1 and DB_2 were captured during routine daily activities. The young subjects were asked to perform 16 routine daily activities, consisting of 5 static and 11 non-static activities, 5 times each. The elderly subjects were asked to perform 7 routine activities, comprising 6 static activities and 1 non-static activity, 2 times each. The lists of static activities and non-static activities are shown in Table 1 and Table 2 respectively. Table 3 presents detailed hardware specifications of a wireless BSN node used in this study.

Maejo Int. J. Sci. Technol. **2016**, *10*(02), 127-141; doi: 10.14456/mijst.2016.12

Table 1. Static activity list

No.		Activity type	DB_1	DB_2
1	Sitting	on a chair	✓	✓
2		on a chair while reading a book	✓	-
3		on a bed	-	✓
4	Lying	on back	✓	✓
5		on left side	-	✓
6		on right side	-	✓
7	Standing	still (no movement)	✓	✓
8		while deeply breathing	✓	-

Table 2. Non-static activity list

No.	Activity type		DB_1	DB_2
1	Up and down movement of	right arm	✓	-
2		left arm	✓	-
3		both arms	✓	-
4	Jumping up and down on the floor		✓	-
5	Twisting left-right-left at the waist		✓	-
6	Bending	forward	✓	-
7		backward	✓	-
8	Walking	on the floor	✓	✓
9		upstairs	✓	-
10		downstairs	✓	-
11	Jogging		✓	-

Table 3. Detailed hardware specifications of wireless BSNs

Hardware	Module	Specification
CPU (TI MSP130F149)	Clock	8 Kilobytes
	RAM	2 Kilobytes
	Flash memory	60 Kilobytes
	Analogue-to-Digital converter resolution	12 Bits
Radio transceiver (Chipcon CC2420)	Communication standard	Wireless IEEE 802.15.4
	Bandwidth	250 Kilobits per second
	Frequency	2.4 Giga Hertz
External storage	EEPROM	4 Megabytes

Maejo Int. J. Sci. Technol. **2016**, *10*(02), 127-141; doi: 10.14456/mijst.2016.12

The arrhythmia database of MIT-BIH public standard [22] was used as the third database, DB_3. It consists of 48 ECG recordings acquired at 360 Hz with 11-bit resolution using holters. The recordings were captured from 47 subjects (22 females and 25 males) aged between 32-89 years. Each of them was an inpatient or outpatient of Beth Israel Hospital between 1975-1979. As suggested by a report published by the Association for the Advancement of Medical Instrumentation (AAMI) [23], four ECG recordings in DB_3 were excluded (i.e. the recordings 102, 104, 107 and 217) since they contained paced beats. The remaining 44 recordings were used in this study.

ECG Signal Annotations

In order to annotate ECG signals with quality levels, the quality classes suggested by Clifford et al. [24] were applied. Signals without any noise or with some minor noises, i.e. signals in classes A and B [24], were considered as 'high-quality' signals. Signals that could hardly be interpretable with confidence, i.e. those in classes D and F [24], were regarded as 'low-quality' signals. To avoid confusion due to different quality levels, quality labelling was performed at the level of segments. ECG signals from DB_1, DB_2 and DB_3 were decomposed into small segments, each of which was 5 seconds long. A segment was labelled as 'low-quality' if 40% or more of its ECG signal samples (totalling approximately 2 seconds) were assessed as low quality. It was labelled as 'high-quality' otherwise. Figure 1 illustrates the difference between a high-quality signal segment and low-quality signal segments caused by some common types of ECG noises [9]. The distribution of signal qualities in each database is shown in Table 4.

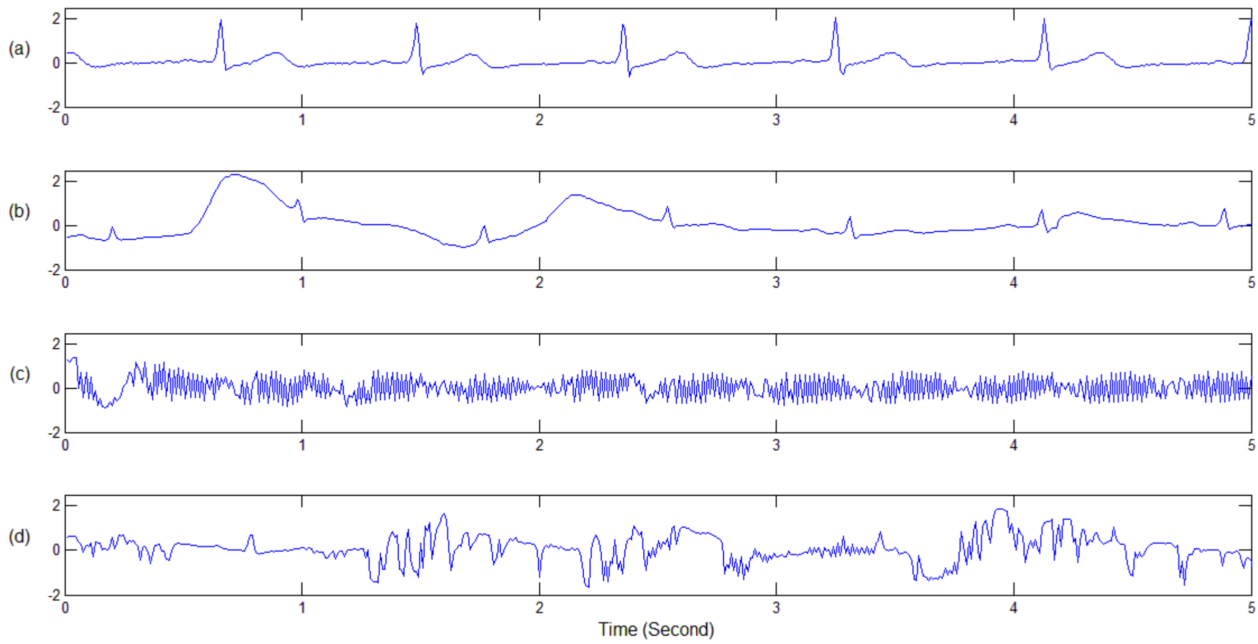

Figure 1. Examples of ECG signals in DB_1: a high-quality segment (a), compared with low-quality segments caused by baseline drift (b), power line interference (c) and motion artefacts (d)

Maejo Int. J. Sci. Technol. **2016**, *10*(02), 127-141; doi: 10.14456/mijst.2016.12

Table 4. No. of segments labelled with each quality level in DB_1, DB_2 and DB_3

Database	Signal quality level		Total
	Low	High	
DB_1	287	2,219	2,506
DB_2	87	382	469
DB_3	-	15,884	15,884

Feature Extraction

Based on our observation and analysis of ECG signals, the sum of signal amplitudes in a signal portion corrupted by noises, e.g. baseline-drift noises and motion artefacts, was usually significantly greater than that in a noiseless signal portion (see Figure 1 for example). Amplitudes of ECG signals can therefore be used as features for separating noisy signal portions from noiseless ones. Signal-amplitude-based features (i.e. statistical values of signal amplitudes) were also employed for signal quality classification in several studies [11, 12, 14, 25].

In order to minimise the variation among subjects in different databases, ECG signals in a database (DB_1, DB_2 or DB_3) were normalised with median and standard deviation values calculated over the same database. For signal quality assessment, two levels of statistical features, i.e. window-based temporal features and segment-based features (5 seconds per one segment), were extracted. Six window-based temporal features, including mean, variance and slope of signal amplitudes, were first extracted from normalised ECG signals using a window of size 1 second, shifted at each step by 0.5 second. The statistical values of the window-based temporal features were then used for extracting 36 segment-based features. Four additional segment-based features were calculated from the statistical values of signal amplitudes. Tables 5 and 6 show the window-based temporal features and segment-based features used in this study.

Feature Selection

In machine-learning-based classification, the feature selection is an important data processing step for eliminating irrelevant and redundant information, and it can often enhance the classification performance. Hall [26] proposed a correlation-based feature-selection (CFS) algorithm that is both fast and effective for a feature section [27]. CFS is a heuristic method for finding a subset of features that are strongly correlated with a particular class while being uncorrelated with other classes. CFS has been widely used for reducing a feature space and determining appropriate features in several studies, e.g. cardiac arrhythmia classification using ECG signals [28, 29], sleep apnea detection using ECG signals and saturation of peripheral oxygen signals [30], sleep-stage classification using ECG signals [31], and activity recognition using acceleration signals [32]. In this study CFS with the best first-search strategy was applied to selection of an appropriate feature subset for signal quality classification. By applying the CFS to segment-based features in DB_1, 5 features, i.e. F_2, F_5, F_8, F_{20} and F_{38}, were selected from the 40 original features. These selected features are given in Table 7.

Maejo Int. J. Sci. Technol. **2016**, *10*(02), 127-141; doi: 10.14456/mijst.2016.12

Table 5. Window-based temporal features

Feature	Description
T_1	Mean of ECG amplitudes
T_2	Variance of ECG amplitudes
T_3	Summation of ECG amplitude slopes
T_4	Mean of absolute ECG amplitudes
T_5	Variance of absolute ECG amplitudes
T_6	Summation of slopes of absolute ECG amplitudes

Table 6. Segment-based features (calculated from window-based temporal features and signal amplitudes within each 5-second segment)

Feature	Description
F_1-F_3	Means of T_1, T_2 and T_3 respectively
F_4-F_6	Variances of T_1, T_2 and T_3 respectively
F_7-F_9	Slopes of T_1, T_2 and T_3 respectively
F_{10}-F_{12}	Maximum values of T_1, T_2 and T_3 respectively
F_{13}-F_{15}	Minimum values of T_1, T_2 and T_3 respectively
F_{16}-F_{18}	Differences between maximum and minimum values of T_1, T_2 and T_3 respectively
F_{19}-F_{21}	Means of T_4, T_5 and T_6 respectively
F_{22}-F_{24}	Variances of T_4, T_5 and T_6 respectively
F_{25}-F_{27}	Slopes of T_4, T_5 and T_6 respectively
F_{28}-F_{30}	Maximum values of T_4, T_5 and T_6 respectively
F_{31}-F_{33}	Minimum values of T_4, T_5 and T_6 respectively
F_{34}-F_{36}	Differences between maximum and minimum values of T_4, T_5 and T_6 respectively
F_{37}	Mean of absolute ECG amplitudes
F_{38}	Variance of ECG amplitudes
F_{39}	Summation of ECG amplitude slopes
F_{40}	Difference between maximum and minimum ECG amplitudes

Table 7. Segment-based features selected by CFS algorithm

Feature	Description
F_2	Mean of T_2 within 5-second segment
F_5	Variance of T_2 within 5-second segment
F_8	Slope of T_2 within 5-second segment
F_{20}	Mean of T_5 within 5-second segment
F_{38}	Variance of signal amplitudes within 5-second segment

Maejo Int. J. Sci. Technol. **2016**, *10*(02), 127-141; doi: 10.14456/mijst.2016.12

Signal Quality Classification

Four well-known machine-learning-based algorithms implemented in Java [27], namely IB*k* (Instance-based Learning), J48 (Decision Tree), MLP (Multilayer Perceptron) and PART (Rule Induction), were used for signal quality classification in this study. The IB*k*, also known as lazy learning, performs a classification based on a comparison between new instances (test data) and known instances stored in the memory (training data). A *k*-nearest neighbour algorithm is a basic IB*k* method used for implementing an IB*k* classifier. The J48 is an implementation of a well-known J48 algorithm, i.e. a C4.5 algorithm. In J48, a greedy algorithm is adopted for constructing decision trees and for reduced-error pruning. The MLP algorithm is one of the most versatile artificial neural network models. It is a feed-forward model for mapping input data to an appropriate output. It can solve non-linearly separable problems and has been widely used for pattern recognition and classification. The PART algorithm is used for constructing a set of rules based on selection of leaf nodes with the largest instance coverage in partial C4.5 decision trees.

To evaluate the performance of the obtained signal quality classifiers, a leave-one-out cross-validation method [33] was applied to the ECG recordings in DB_1, which were acquired from 10 subjects. In each cross-validation step ECG signals from nine subjects were employed for constructing a classification model, and ECG signals from the remaining subject were used for testing. ECG recordings in DB_2 and DB_3 were used as test data in order to evaluate the robustness and generalisation capacity of the signal quality classifier constructed from the entire DB_1. Table 8 summarises the utilisation of each database.

Table 8. Database utilisation for evaluating signal quality classifier

Experiment	**Utilisation**		
	DB_1 (2,506 segments)	**DB_2 (469 segments)**	**DB_3 (15,884 segments)**
#1	Leave-one-out cross validation	-	-
#2	Training data	Test data	-
#3	Training data	-	Test data

EXPERIMENTS AND RESULTS

The performance of signal quality assessment is measured using four standard measures: sensitivity, specificity, selectivity and accuracy [34]. In this study true positives and true negatives are signal segments accurately assessed as 'low-quality' and 'high-quality' respectively, while false positives and false negatives are those inaccurately assessed as 'low-quality' and 'high-quality' respectively.

Referring to Table 8, ECG signal recordings from the databases DB_1, DB_2 and DB_3 were employed for different experimental objectives. Signal recordings from DB_1 were used for evaluating the performance of our proposed signal quality classification framework using a leave-one-out cross validation. In addition to such cross validation on DB_1 itself, signals from DB_1 were also used to construct a signal quality assessment model for classifying unseen signals in DB_2 and DB_3 for the purpose of evaluating the robustness and generalisation capacity of the model. The

Maejo Int. J. Sci. Technol. **2016**, *10*(02), 127-141; doi: 10.14456/mijst.2016.12

database DB_3 was also used for evaluating the performance of the model in arrhythmia signal recordings.

To construct the signal quality classification model, four well-known algorithms, i.e. IB*k*, J48, MLP and PART, were used with default parameter values of Weka (API version 3.6.5) [27]. DB_1 was employed for evaluating the performance of the four algorithms. Using the leave-one-out cross validation, Table 9 shows a performance comparison for the four algorithms. When all features (40 features, cf. Table 6) were used, the J48 algorithm gave the highest accuracy of 96.73%, with the sensitivity of 82.58%, the specificity of 98.56% and the selectivity of 88.10%. When the selected features (5 features, cf. Table 7) were used, the MLP algorithm yielded the highest accuracy of 97.37%, with the sensitivity, specificity and selectivity of 83.62%, 99.14% and 92.66% respectively. Table 10 shows the overall classification performance of the MLP classifier.

Table 11 shows the confusion matrix for static and non-static activities obtained using the MLP classifier constructed from the selected features in DB_1. The accuracy values are 98.43% and 96.72% for static and non-static activities respectively. The results demonstrate that the MLP signal quality assessment model can reliably classify ECG signals captured while the subjects are performing daily routine activities, with an accuracy of more than 95%.

Table 9. Performance comparison of signal quality assessment using machine-learning-based algorithms on DB_1

Algorithm	Using all features				Using selected features			
	SEN	**SPE**	**SEL**	**ACC**	**SEN**	**SPE**	**SEL**	**ACC**
IB*k* ($k = 1$)	75.61%	97.70%	80.97%	95.17%	83.97%	97.84%	83.39%	96.25%
IB*k* ($k = 3$)	75.96%	98.69%	88.26%	96.09%	83.28%	98.65%	88.85%	96.89%
J48	**82.58%**	**98.56%**	**88.10%**	**96.73%**	81.88%	99.23%	93.25%	97.25%
MLP	79.44%	98.87%	90.12%	96.65%	**83.62%**	**99.14%**	**92.66%**	**97.37%**
PART	79.09%	98.56%	87.64%	96.33%	82.58%	99.01%	91.51%	97.13%

Note: SEN = sensitivity, SPE = specificity, SEL = selectivity, ACC = accuracy, *k* = the number of nearest neighbours for Instance-based Learning

Table 10. Classification performance of MLP using DB_1

Signal quality level		Using all features		Using selected features	
		Low	**High**	**Low**	**High**
Actual	Low	228	59	240	47
	High	25	2194	19	2200
Sensitivity		79.44%		83.62%	
Specificity		98.87%		99.14%	
Selectivity		90.12%		92.66%	
Accuracy		96.65%		97.37%	

Maejo Int. J. Sci. Technol. **2016**, *10*(02), 127-141; doi: 10.14456/mijst.2016.12

Table 11. Confusion matrix for static and non-static activities in DB_1 using MLP with selected features

Activity type	Quality level	Predicted		Accuracy
		Low	High	
Static	Low	43	15	98.43%
	High	0	895	
Non-static	Low	197	32	96.72%
	High	19	1305	

To implement the signal classification model for real-time continuous monitoring, a feature set of small size is preferred. Based on the results shown in Table 9, the MLP algorithm with the five selected features was chosen for classifying signal quality levels. In order to evaluate its robustness, the MLP classifier constructed from DB_1 (the young-subject database) was employed to classify ECG signals from DB_2 (the elderly-subject database) and DB_3 (the standard arrhythmia database).

Table 12 presents the performance of the MLP model evaluated on DB_2. The overall accuracy values are 93.39% and 94.67% using all features and selected features respectively. Table 13 shows the relation between predicted signal quality levels and actual activity types in DB_2. For static and non-static activities, the overall accuracy of 94.30% and 96.39% respectively are achieved.

The performance of the MLP classifier using DB_3 is shown in Table 14, with average accuracy values of 93.65% and 98.05% when all features and selected features respectively are used. Since all ECG recordings in DB_3 were captured in a hospital-based environment with no activity of daily living being involved, all ECG signals in this dataset are annotated as 'high-quality'. Sensitivity and selectivity are therefore not calculated.

Table 12. Classification performance of MLP using DB_2

Signal quality level		Using all features		Using selected features	
		Low	High	Low	High
Actual	Low	76	11	80	7
	High	20	362	18	364
Sensitivity		87.36%		91.95%	
Specificity		94.76%		95.29%	
Selectivity		79.17%		81.63%	
Accuracy		93.39%		94.67%	

Maejo Int. J. Sci. Technol. **2016**, *10*(02), 127-141; doi: 10.14456/mijst.2016.12

Table 13. Confusion matrix for static and non-static activities in DB_2 using MLP with selected features

Activity type	Quality level	Predicted		Accuracy
		Low	High	
Static	Low	68	5	94.30%
	High	17	296	
Non-static	Low	12	2	96.39%
	High	1	68	

Table 14. Classification performance of MLP using DB_3

Signal quality level		Using all features		Using selected features	
		Low	High	Low	High
Actual	Low	0	0	0	0
	High	1,009	14,875	309	15,573
Sensitivity		N/A		N/A	
Specificity		93.65%		98.05%	
Selectivity		N/A		N/A	
Accuracy		93.65%		98.05%	

With reference to Table 14, 309 segments are predicted as 'low-quality' and 15,573 segments as 'high-quality', using MLP with selected features. These low-quality and high-quality segments (5 seconds each) consist of 2,416 and 98,540 heartbeats respectively. Table 15 shows the association between five AAMI heartbeat classes [23], which are standard classes widely used in ECG classification [35-37], and the predicted signal quality levels. The 2,416 heartbeats predicted as 'low-quality' are divided into 1,808 non-ectopic beats, 7 supraventricular ectopic beats, 333 ventricular ectopic beats, 256 fusion beats and 12 unknown beats. The non-ectopic beats classified as 'low-quality' are obtained mainly from two ECG recordings in DB_3, i.e. the recordings 116 and 213. Most of ventricular ectopic beats and fusion beats that are classified as 'low-quality' belong to the recording 213. A closer investigation reveals that the ECG amplitude values of the recordings 116 and 213 are much higher than those of the remaining recordings in DB_3 (the other 42 recordings). ECG segments in recordings with high outlier amplitude values, such as the recordings 116 and 213, can be excluded by some additional preprocessing steps, e.g. using threshold-based rules.

Table 16 provides a summary of related studies on ECG signal quality classification. In this study our machine-learning-based framework was evaluated on ECG signals captured through wireless BSNs from young subjects (DB_1) and elderly subjects (DB_2) while they were performing daily routine activities, and also on ECG signals obtained from the publicly available MIT-BIH arrhythmia database (DB_3). Using the MLP classifier with a combination of window-based temporal and segment-based features, accuracy values of 97.4%, 94.7% and 98.1% were achieved on DB_1,

Maejo Int. J. Sci. Technol. **2016**, *10*(02), 127-141; doi: 10.14456/mijst.2016.12

DB_2 and DB_3 respectively. As demonstrated by these results, our framework performs well compared to existing related studies (cf. Table 16) and can potentially be used for signal quality assessment in continuous ECG monitoring.

Table 15. AAMI heartbeat types associated with beats with predicted signal qualities from DB_3

AAMI class	Total beats	Predicted signal quality	
		Low	High
Non-ectopic beats	89,896	1,808	88,088
Supraventricular ectopic beats	2,773	7	7,463
Ventricular ectopic beats	7,470	333	2,440
Fusion beats	802	256	546
Unknown beats	15	12	3
Total	**100,956**	**2,416 (2.39%)**	**98,540 (97.61%)**

Table 16. Comparison of existing studies on signal quality classification

Ref.	Database used	Device type	Features/Criteria	Method	ACC
[11] (2011)	PhysioCha2011	Mobile phones	5 threshold-based rules concerning signal amplitude contents	Rule-based system	86.8%
[12] (2011)	PhysioCha2011	Mobile phones	6 threshold-based rules concerning signal amplitude contents + segment-based features based on covariance matrices, kurtosis values and means of signal amplitudes	Rule-based system + SVM	91.8%
[13] (2011)	PhysioCha2011	Mobile phones	35 segment-based features based on signal frequency contents	EDTs	90.4%
[14] (2012)	PhysioCha2011	Mobile phones	5 threshold-based rules concerning signal amplitude and signal frequency contents	Rule-based system	91.2%
[17] (2012)	ECG signal recordings captured from 12 young subjects during 5 ADL	Contactless ECG devices	17 segment-based features based on statistical values of signal amplitudes	SVM	91.0%
[25] (2014)	PhysioCha2011	Mobile phones	Signal quality indices based on combination of energy, concavity and correlation features	ANN	93.6%
This study	ECG signal recordings captured from 10 young subjects during 16 ADL	Wireless BSNs	5 segment-based features based on two levels of statistical features, i.e. window-based temporal features and segment-based features	MLP	97.4%
	ECG signal recordings captured from 10 elderly subjects during 11 ADL				94.7%
	MIT-BIH arrhythmia database	Hospital-based holters			98.1%

Note: ADL = activities of daily living, ACC = accuracy, SVM = Support Vector Machine, EDTs = Ensembles of Decision Trees, ANN = Artificial Neural Network, MLP = Multilayer Perceptron

Maejo Int. J. Sci. Technol. **2016**, *10*(02), 127-141; doi: 10.14456/mijst.2016.12

CONCLUSIONS

We have presented a machine-learning-based method for automatic ECG signal quality assessment in continuous wireless monitoring. The experimental results have shown that the proposed method yields an average accuracy of more than 96%. The method can thus be reliably applied to improve the performance of arrhythmia classification in continuous ECG monitoring by reducing false arrhythmia alarms arising from low-quality signal portions.

ACKNOWLEDGEMENTS

This work was supported by (1) the Research Institute of Rangsit University, (2) the Thailand Research Fund (TRF) under Royal Golden Jubilee Ph.D. Programme, (3) the National Research University Project of Thailand Office of Higher Education Commission and (4) the Centre of Excellence in Intelligent Informatics, Speech and Language Technology and Service Innovation (CILS), Thammasat University. It was also partially supported by the Anandamahidol Foundation.

REFERENCES

1. A. Milenković, C. Otto and E. Jovanov, "Wireless sensor networks for personal health monitoring: Issues and an implementation", *Comput. Commun.*, **2006**, *29*, 2521-2533.
2. A. Pantelopoulos and N. G. Bourbakis, "A survey on wearable sensor-based systems for health monitoring and prognosis", *IEEE Trans. Syst. Man Cybern. C*, **2010**, *40*, 1-12.
3. S. Patel, H. Park, P. Bonato, L. Chan and M. Rodgers, "A review of wearable sensors and systems with application in rehabilitation", *J. Neuroeng. Rehabil.*, **2012**, *9*, 21 (doi: 10.1186/1743-0003-9-21).
4. N. Pannurat, S. Thiemjarus and E. Nantajeewarawat, "Automatic fall monitoring: A review", *Sensors*, **2014**, *14*, 12900-12936.
5. WHO, "Global Status Report on Non-communicable Diseases 2014", World Health Organization, Geneva, **2014**.
6. J. J. Oresko, Z. Jin, J. Cheng, S. Huang, Y. Sun, H. Duschl and A. C. Cheng, "A wearable smartphone-based platform for real-time cardiovascular disease detection via electrocardiogram processing", *IEEE Trans. Inform. Technol. Biomed.*, **2010**, *14*, 734-740.
7. S. Winkler, M. Schieber, S. Lücke, P. Heinze, T. Schweizer, D. Wegertseder, M. Scherf, H. Nettlau, S. Henke, M. Braecklein, S. D. Anker and F. Koehler, "A new telemonitoring system intended for chronic heart failure patients using mobile telephone technology--Feasibility study", *Int. J. Cardiol.*, **2011**, *153*, 55-58.
8. A. Andreoli, R. Gravina, R. Giannantonio, P. Pierleoni and G. Fortino, "SPINE-HRV: A BSN-based toolkit for heart rate variability analysis in the time-domain", *Lect. Notes. Electr. Eng.*, **2010**, *75*, 369-389.
9. M. Z. U. Rahman, R. A. Shaik and D. V. R. K. Reddy, "Adaptive noise removal in the ECG using the Block LMS algorithm", Proceedings of 2nd International Conference on Adaptive Science and Technology, **2009**, Accra, Ghana, pp.380-383.
10. F. Schmid, M. S. Goepfert and D. A. Reuter, "Patient monitoring alarms in the ICU and in the operating room", *Crit. Care*, **2013**, *17*, 216 (doi: 10.1186/cc12525).
11. V. Chudacek, L. Zach, J. Kuzilek, J. Spilka and L. Lhotska, "Simple scoring system for ECG quality assessment on android platform", Proceedings of Computing in Cardiology Conference, **2011**, Hangzhou, China, pp.449-451.

Maejo Int. J. Sci. Technol. **2016**, *10*(02), 127-141; doi: 10.14456/mijst.2016.12

12. J. Kuzilek, M. Huptych, V. Chudacek, J. Spilka and L. Lhotska, “Data driven approach to ECG signal quality assessment using multistep SVM classification”, Proceedings of Computing in Cardiology Conference, **2011**, Hangzhou, China, pp.453-455.
13. S. Zaunseder, R. Huhle and H. Malberg, “CinC challenge—Assessing the usability of ECG by ensemble decision trees”, Proceedings of Computing in Cardiology Conference, **2011**, Hangzhou, China, pp.277-280.
14. L. Johannesen and L. Galeotti, “Automatic ECG quality scoring methodology: Mimicking human annotators”, *Physiol. Meas.*, **2012**, *33*, 1479-1489.
15. I. Silva, G. B. Moody and L. Celi, “Improving the quality of ECGs collected using mobile phones: The PhysioNet/Computing in cardiology challenge 2011”, Proceedings of Computing in Cardiology Conference, **2011**, Hangzhou, China, pp.273-276.
16. B.-S. Baek, D.-M. Kim, F. Bashir and J.-Y. Pyun, “Real life applicable fall detection system based on wireless body area network”, Proceedings of IEEE Consumer Communications and Networking Conference, **2013**, Las Vegas, USA, pp.62-67.
17. J. Schumm, B. Arnrich and G. Troster, “ECG monitoring in an airplane seat: Appraising the signal quality”, *IEEE Pervasive Comput.*, **2012**, *11*, 28-34.
18. N. K. Suryadevara, M. T. Quazi and S. C. Mukhopadhyay, “Intelligent sensing systems for measuring wellness indices of the daily activities for the elderly”, Proceedings of 8th International Conference on Intelligent Environments, **2012**, Guanajuato, Mexico, pp.347-350.
19. T. Pawar, S. Chaudhuri and S. P. Duttagupta, “Body movement activity recognition for ambulatory cardiac monitoring”, *IEEE Trans. Biomed. Eng.*, **2007**, *54*, 874-882.
20. T. Pawar, N. S. Anantakrishnan, S. Chaudhuri and S. P. Duttagupta, “Transition detection in body movement activities for wearable ECG”, *IEEE Trans. Biomed. Eng.*, **2007**, *54*, 1149-1152.
21. S. Thiemjarus and G.-Z. Yang, “Context-aware sensing”, in “Body Sensor Networks” (Ed. G.-Z. Yang), Springer, London, **2006**, Ch.9.
22. G. B. Moody and R. G. Mark, “The impact of the MIT-BIH arrhythmia database”, *IEEE Eng. Med. Biol.*, **2001**, *20*, 45-50.
23. Association for the Advancement of Medical Instrumentation, “ANSI/AAMI/ISO EC57:1998/(R)2008 testing and reporting performance results of cardiac rhythm and ST segment measurement algorithms”, **2012**, http://my.aami.org/aamiresources/previewfiles/EC57_1212_preview.pdf (Accessed: April 2016).
24. G. D. Clifford, J. Behar, Q. Li and I. Rezek, “Signal quality indices and data fusion for determining clinical acceptability of electrocardiograms”, *Physiol. Meas.*, **2012**, *33*, 1419-1433.
25. H. Naseri and M. R. Homaeinezhad, “Electrocardiogram signal quality assessment using an artificially reconstructed target lead”, *Comput. Meth. Biomech. Biomed. Eng.*, **2015**, *18*, 1126-1141.
26. M. A. Hall, “Correlation-based feature subset selection for machine learning”, *PhD Thesis*, **1998**, University of Waikato, New Zealand.
27. R. R. Bouckaert, E. Frank, M. A. Hall, G. Holmes, B. Pfahringer, P. Reutemann and I. H. Witten, “WEKA-experiences with a Java open-source project”, *J. Mach. Learn. Res.*, **2010**, *11*, 2533-2541.
28. M. Mitra and R. K. Samanta, “Cardiac arrhythmia classification using neural networks with selected features”, *Procedia Technol.*, **2013**, *10*, 76-84.

Maejo Int. J. Sci. Technol. **2016**, *10*(02), 127-141; doi: 10.14456/mijst.2016.12

29. U. Arıkan and F. Gürgen, "Discrimination ability of time-domain features and rules for arrhythmia classification", *Math Comput. Appl.*, **2012**, *17*, 111-120.
30. B. Xie and H. Minn, "Real-time sleep apnea detection by classifier combination", *IEEE Trans. Inform. Technol. Biomed.*, **2012**, *16*, 469-477.
31. A. Noviyanto, S. M. Isa, I. Wasito and A. M. Arymurthy, "Selecting features of single lead ECG signal for automatic sleep stages classification using correlation-based feature subset selection", *Int. J. Comput. Sci.*, **2011**, *8*, 139-148.
32. N. A. Capela, E. D. Lemaire and N. Baddour, "Feature selection for wearable smartphone-based human activity recognition with able bodied, elderly, and stroke patients", *PLoS ONE*, **2015**, *10*, e0124414 (doi: 10.1371/journal.pone.0124414).
33. C. Sammut and G. I. Webb, "Encyclopedia of Machine Learning", Springer, Boston (MA), **2010**, pp.600-601.
34. Y. Kutlu and D. Kuntalp, "Feature reduction method using self-organizing maps", Proceedings of 6th International Conference on Electrical and Electronics Engineering, **2009**, Bursa, Turkey, pp.129-132.
35. T. Ince, S. Kiranyaz and M. Gabbouj, "A generic and robust system for automated patient-specific classification of ECG signals", *IEEE Trans. Biomed. Eng.*, **2009**, *56*, 1415-1426.
36. T. Mar, S. Zaunseder, J. P. Martinez, M. Llamedo and R. Poll, "Optimization of ECG classification by means of feature selection", *IEEE Trans. Biomed. Eng.*, **2011**, *58*, 2168-2177.
37. R. J. Martis, U. R. Acharya and L. C. Min, "ECG beat classification using PCA, LDA, ICA and discrete wavelet transform", *Biomed. Signal Proc. Control*, **2013**, *8*, 437-448.