A *k*NN Approach for ECG Signal Quality Classification

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***Abstract*—The quality of Electrocardiogram (ECG) signal recordings is importantly considered in continuous monitoring systems, especially in monitoring systems using wireless devices, e.g., wireless Body Sensor Networks (BSNs). Patient's ECG signal recordings with low quality frequently cause in high false alarms in the Cardiac Care Unit. Furthermore, ECG signals acquired from the wireless BSNs while subjects perform activities of daily living (ADLs) can be often deteriorated by baseline drift noises and motion artifacts, occurring from human body movements. Therefore, for improving the performance of continuous monitoring systems using BSNs, low-quality signals should be detected and then should be suppressed from the systems. This paper presents an automatic approach for signal quality classification using a simple instance-based machine learning algorithm, i.e., *k*-Nearest Neighbor (*k*NN), and statistical ECG-based features. In data acquisition, a wireless BSN node was used for collecting ECG signals from 10 subjects while performing ADLs. For data annotation, the obtained signals were divided into small segments (each 5 seconds long) and these segments are annotated with good-quality and bad-quality labels depending on their signal quality levels. The average evaluation results of signal quality classification are 96.87%, 84.79%, and 98.44%, for accuracy, sensitivity, and specificity, respectively.**

***Index Terms*—ECG signal quality classification, wireless body sensor networks, machine learning, noise and artifact detection.**

I. Introduction

As reported by the World Health Federation [1], over 70 percent of all cardiac emergencies, e.g., heart attacks and ischaemic strokes, occur in the home. Cardiovascular diseases claim 17.1 million lives, which are 82% of deaths occurring in low-income and middle-income countries. In order to prevent occurrence of such deaths, suitable cardiac monitoring systems that can be used for monitoring patients in the home environments are thus essentially required, e.g., continuous cardiac monitoring systems using wireless devices. In [2]-[5], continuous cardiac monitoring systems using wireless ECG sensors have been developed, with effective results being reported. Nevertheless, ECG signals continuously acquired using wireless sensors during activities of daily living (ADLs) are frequently deteriorated by several types of noises and artifacts, e.g., baseline drift noises and motion artifacts, causing from human body movements. These noises and artifacts can affect the quality of ECG signals and lead to occurring high rates of false alarms in continuous monitoring [6]-[8]. Therefore, for improving the performance of continuous ECG monitoring using wireless sensors during ADLs, further investigations on classifying noisy signals from noiseless signals are required.

Manuscript received February 11, 2016; revised July 14, 2016. This work was supported by the Research Institute of Rangsit University and the Thailand Research Fund (TRF), under Royal Golden Jubilee Ph.D. Program Grant No. PHD/0225/2551.

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ECG signal quality classification have been reported in several studies [9]-[11]. Chudacek *et al.* [9] developed a noise detection system using a rule-base expert system. In order to detect common noises and artifacts in ECG signals, e.g., baseline drift noises and motion artifacts, features extracted from signal amplitudes were employed for constructing 5 noise classification rules, which were used to detect signal quality levels. In [10], Kuzilek *et al.* proposed a multi-step approach for signal quality classification using a threshold-based rule and a Support Vector Machine (SVM) algorithm. In the first step, statistical features calculated from ECG signal amplitudes were used for constructing 6 rules. Each rule added one point of a quality score to each signal recording when it satisfied the condition. In the second step, a SVM classifier with features including kurtosis values and covariance matrices was used to determine a quality score of each signal recording. In the last step, a signal recording was determined whether that recording should be rejected based on the quality scores of the previous two steps. In [11], Johannesen *et al.* proposed a multi-step method for classifying the quality of ECG signals. Based on signal amplitude values, bad-quality signal recordings causing by lead connection problems, e.g., large amplitude and signal absence, were first exclude. Next, 3 quality scores were calculated from the levels of ECG noises. Finally, a rule set was used for determining whether a signal recording should be accepted.

In the above studies [9]-[11], ECG signals obtained from the Physionet Challenge 2011 database [12], were used for their evaluation purposes. The database consists of signal recordings captured from normal subjects using mobile devices. Further evaluation on ECG signal recordings captured while subjects are performing ADLs is thus required.

This paper presents an approach for signal quality classification in continuous cardiac monitoring using wireless sensors. ECG signals captured using a wireless BSNs from 10 healthy volunteers while performing 16 ADLs, e.g., standing, walking, and jogging, were used for validating the proposed approach. To annotate ECG signals with quality levels as suggested in [13], the entire signals were divided into small segments (each 5 seconds long). Using a *k*-Nearest Neighbor algorithm and statistical features, 5-second ECG segments were classified into good-quality and bad-quality levels.

II. Dataset and Signal Annotation

In this study, ECG signal recordings were captured though

doi: 10.18178/ijiee.2016.6.4.636

a wireless BSN node from 10 healthy volunteers (7 men and 3 women), at a sampling rate of 100 Hz. The volunteers were monitored 10 minutes for 5 times while they were performing ADLs. They were asked to perform 5 non-body-movement activities, i.e., sitting, reading, lying, standing, and deep breathing, and 11 body-movement activities, i.e., up and down movement of the right arm and that of the left arm, up and down movement of both arms, jumping, twisting left-right-left body movement at the waist, bending forward, bending backward, walking, climbing upstairs, climbing downstairs, and jogging. Fig. 1 presents the BSN node and the experimental setup for signal data collection.

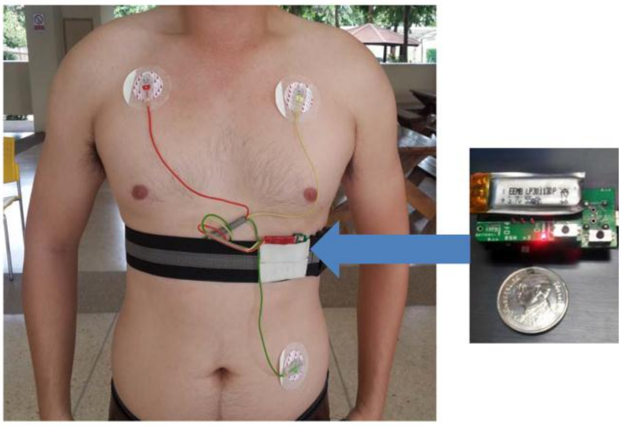

Fig. 1. A wireless BSN node with an ECG sensor attached to a human body.

Based on the signal-quality schemes reported in [13], the entire ECG signal recordings acquired using BSNs were manually annotated with 2 quality levels, i.e., good quality (classes A and B in [13]) and bad quality (classes D and E in [13]). Signals in each ECG recording were divided into small segments, each 5 seconds long, and each of these segments was labeled as either high or low quality. Fig. 2 shows good-quality and bad-quality signals used in this study. Fig. 3 presents the distribution of ECG signal quality levels per subject.

III. Methods

A. Data Normalization

For dealing with ECG signals collected from different subjects, data normalization is essential in order to transform signal-amplitude values from their original values into the comparative scales. In this study, the Z-score normalization was used and given by

$$Y(s) = \frac{X(s) - \mu}{\sigma}$$

where $Y(s)$ and $X(s)$ are the normalized ECG signals and the signal amplitude at the s^{th} sample, respectively. μ and σ are the mean and the standard deviation of the signals, respectively.

B. Feature Extraction

As presented in [9]-[11], [14], features relating to signal amplitudes can be used for classifying signal quality levels, i.e., good-quality and bad-quality levels. In addition, based on an observation of signals contaminated by baseline drift noises and motion artifacts, the sum of signal amplitudes in bad-quality signals was usually larger than the sum of those in good-quality signals, as shown in Fig. 2.

In this study, statistical features extracted from ECG signals, e.g., mean, variance, and slope, were thus used. First, window-based features were calculated from these statistical features of signal amplitudes of small windows, each of which was derived over a window of size 0.5 seconds, shifted by 0.25 seconds at each processing step. Then, segment-based features (5 seconds per one segment) were extracted from the statistical features of all individual windows and used as features representing the 5-second segment. Total of 40 segment-based features were extracted, i.e., 36 features calculated from window-based feature and 4 segment-based features directly derived from statistical values of signal amplitudes in 5-second segments.

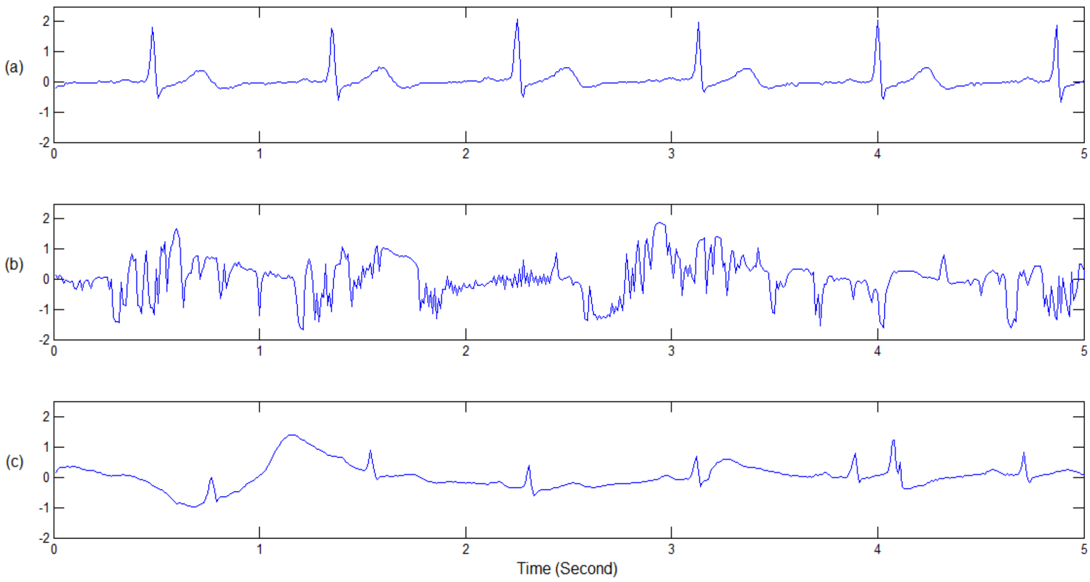

Fig. 2. Examples of ECG signals employed in this study: A good-quality signal portion (a) compared with bad-quality poritons distorioated by motion artifacts (b) and baseline drift noises (c).

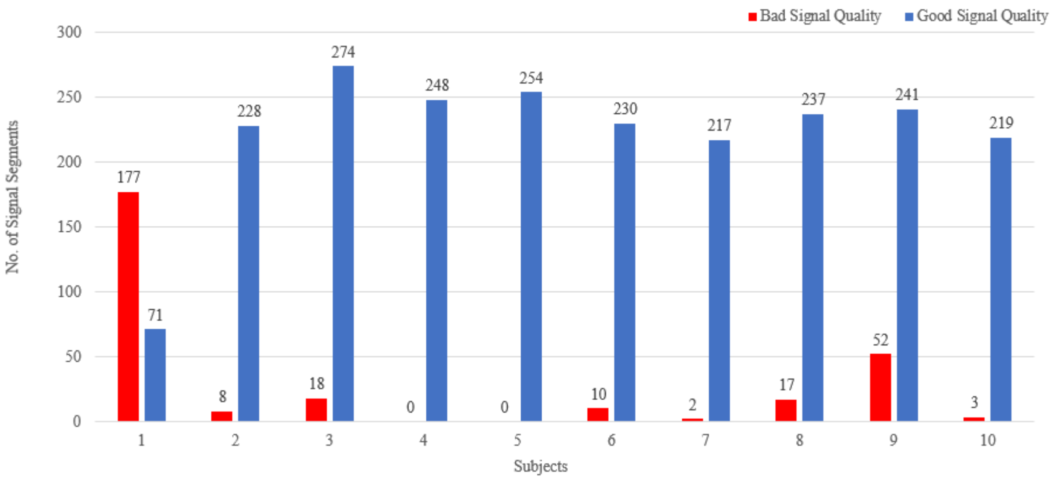

Fig. 3. Distribution of ECG signal quality per subject.

C. Machine-Learning-Based Classification

A simple instance-based learning, a *k*-nearest neighbor (*k*NN) algorithm, was used in this study for constructing signal quality classification models. The *k*NN is one of the most effective non-parmetric. It was also applied in several works relating to ECG signals, e.g., for arrhythmia classification [15]-[17] and for signal quality classification [18]. To implement the *k*NN algorithm, an IB*k* algorithm in Weka API [19] was employed. The values of *k*=1, 3, and 5 were used to construct IB*k* classifiers for determining the optimal value of *k* for signal quality classification.

In order to evaluate the performance of each classification model, a 10-fold cross validation method was used. The whole dataset (2,506 segments) was divided into 10 parts, each having almost the same distribution of samples from each signal-quality labels. Nine sets (2,250 segments) were used for training the classification models and the remaining one set was used for testing and performance evaluation. The process was repeated 10 times and the overall performance of a classifier was calculated by taking the average of 10 folds.

D. Performance Measurement

To measure the performance of each classification model, three standard statistical measures, i.e., Accuracy, Sensitivity, and Specificity, are used [17]. They are defined as:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \times 100\%,$$

$$Sensitivity = \frac{TP}{TP+FN} \times 100\%,$$

$$Specificity = \frac{TN}{TN+FP} \times 100\%,$$

where True Positive (TP) and True Negative (TN) are the number of signal segments correctly predicted as “bad-quality” and “good-quality”, respectively. False Positive (FP) and False Negative (FN) are the number of signal segments incorrectly predicted as “bad-quality” and “good-quality”, respectively.

IV. Experimental Results

Using 10-fold cross validation, Table I presents a performance comparison of the *k*NN algorithms with varying values of *k*. Based on *k*NN with *k*=1 and 5, the obtained accuracy, sensitivity, and specificity values were 96.69%, 85.02%, and 98.20%, respectively. Using *k*NN with *k*=3, the accuracy of 97.25%, the sensitivity of 84.32%, and the specificity of 98.92% were obtained. The average accuracy, sensitivity, and specificity values were 96.87%, 84.79%, and 98.44%, respectively.

TABLE I: Signal Quality Classification Experimental Results

***k*NN Classifier**	**Predicted**		**Measurement**		
	Bad	**Good**	**Accuracy**	**Sensitivity**	**Specificity**
k=1	244	43	96.69%	85.02%	98.20%
	40	2179			
k=3	242	45	97.25%	84.32%	98.92%
	24	2195			
k=5	244	43	96.69%	85.02%	98.20%
	40	2179			
Average Results			96.87%	84.79%	98.44%

The obtained results show that the proposed method can dependably classify ECG signals captured from wireless BSNs while subjects were performing daily routine activities, with the accuracy of more than 96%, the sensitivity of more than 84%, and the specificity of more than 98%. Fig. 4 shows a performance comparison among the *k*-NN classifiers with varying *k* values, *k* = 1, 3, and 5.

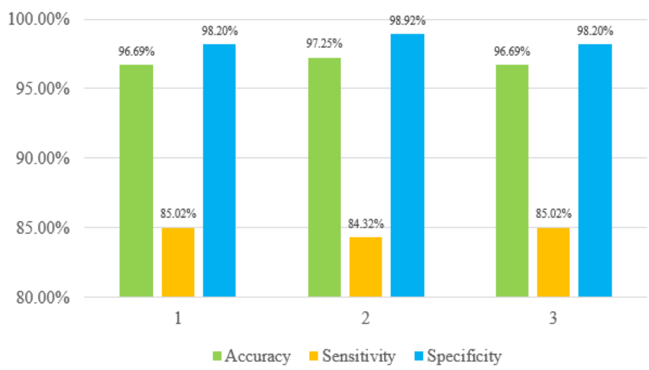

Fig. 4. Performance comparison of signal quality classification using the *k*NN classifiers with varying *k* values.

V. Conclusion

The automatic *k*NN-based approach for classifying signal quality levels in continuous wireless ECG monitoring has been proposed. In this study, ECG datasets captured from human subjects using wireless BSNs were employed. The subjects were asked to perform 16 different ADLs, e.g., sitting, standing, lying, walking, and jogging, in order to create actual noises in free-living environments. The proposed work is different from existing works in the literature that used noisy ECG signals added by mathematic methods. In order to develop continuous monitoring systems using wireless sensors, signals contaminated by noises and artifacts occurring from subjects' body movements should therefore be taken into account.

For constructing signal quality classification models, the *k*NN algorithm, which is a simple instance-based learning algorithm and easy to implement in limited-resource devices, was used. Using 10-fold cross validation, the average obtained results are an accuracy of 96.87%, a sensitivity of 84.79%, and a specificity of 98.44%. The evaluation results showed that the proposed approach can possibly be used for classifying quality levels of ECG signals acquired from wireless sensors and be applied for false alarm reduction in continuous monitoring systems.

Acknowledgment

I would like to express my deep gratitude to Associate Professor Dr. Ekawit Nantajeewarawat at Thammasat University and Assistant Professor Dr. Surapa Thiemjarus at National Electronics and Computer Technology Center for their patient guidance, enthusiastic encouragement, and useful critiques of this research work. My grateful thanks are also extended to Mr. Natthapon Phannurat for his help in collecting data used in this research experiments.

I would also like to extend my thanks to Prof. Huan Liu and the staffs of the Data Mining and Machine Learning laboratory at Arizona State University for their help in offering me the resources in running the program and writing this research paper.

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