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Automated detection and localization of myocardial infarction using electrocardiogram: a comparative study of different leads

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ABSTRACT

Identification and timely interpretation of changes occurring in the 12 electrocardiogram (ECG) leads is crucial to identify the types of myocardial infarction (MI). However, manual annotation of this complex nonlinear ECG signal is not only cumbersome and time consuming but also inaccurate. Hence, there is a need of computer aided techniques to be applied for the ECG signal analysis process. Going further, there is a need for incorporating this computerized software into the ECG equipment, so as to enable automated detection of MIs in clinics. Therefore, this paper proposes a novel method of automated detection and localization of MI by using ECG signal analysis. In our study, a total of 200 twelve lead ECG subjects (52 normal and 148 with MI) involving 611,405 beats (125,652 normal beats and 485,753 beats of MI ECG) are segmented from the 12 lead ECG signals. Firstly, ECG signal obtained from 12 ECG leads are subjected to discrete wavelet transform (DWT) up to four levels of decomposition. Then, 12 nonlinear features namely, approximate entropy (E_a^x), signal energy (Ω^x), fuzzy entropy (E_f^x), Kolmogorov–Sinai entropy (E_{ks}^x), permutation entropy (E_p^x), Renyi entropy (E_r^x), Shannon entropy (E_{sh}^x), Tsallis entropy (E_{ts}^x), wavelet entropy (E_w^x), fractal dimension (F_D^x), Kolmogorov complexity (C_k^x), and largest Lyapunov exponent (E_{LLE}^x) are extracted from these DWT coefficients. The extracted features are then ranked based on the *t* value. Then these features are fed into the *k*-nearest neighbor (KNN) classifier one by one to get the highest classification performance by using minimum number of features. Our proposed method has achieved the highest average accuracy of 98.80%, sensitivity of 99.45% and specificity of 96.27% in classifying normal and MI ECG (two classes), by using *47 features* obtained from lead 11 (V_5). We have also obtained the highest average accuracy of 98.74%, sensitivity of 99.55% and specificity of 99.16% in differentiating the 10 types of MI and normal ECG beats (11 class), by using *25 features* obtained from lead 9 (V_3). In addition, our study results achieved an accuracy of 99.97% in locating inferior posterior infarction by using only lead 9 (V_3) ECG signal. Our proposed method can be used as an automated diagnostic tool for (i) the detection of different (10 types of) MI by using 12 lead ECG signal, and also (ii) to locate the MI by analyzing only one lead without the need to analyze other leads. Thus, our proposed algorithm and computerized system software (incorporated into the ECG equipment) can aid the physicians and clinicians in accurate and faster location of MIs, and thereby providing adequate time available for the requisite treatment decision.

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1. Introduction

1.1. Myocardial infarction

Myocardial infarction (MI) is the silent, rapid and irreversible damage of cardiac muscles following coronary artery blockages. According to World Health Organization (WHO), coronary heart disease (CHD) is the main cause of MI and remains responsible for about one-third or more of all deaths in individuals over age 35 [1,2]. In 2011, CHD alone caused about 1 of every 7 deaths in the USA and around 375,295 Americans died of CHD. Every year, approximated 635,000 Americans have a new coronary attack (first MI) and 300,000 have a recurrent episode (recurrent MI). It is approximated that, each year an additional 155,000 silent first MIs occur [3,4]. According to National Health and Nutrition Examination Survey (NHANES) 2009–2012 data, the prevalence of MI is 2.8% in US adults greater than 20 years of age [3,4].

The expansion of MI is very rapid and if not diagnosed and treated in time, it continues to damage further the myocardial structure and function of left ventricle (LV), because myocardial contractility promotes LV contraction to maintain adequate cardiac output. Projections show that by 2030, the prevalence of CHD will increase approximately 18% from 2015 with estimation of 15.4 million [3,4]. Thus, earlier and faster the MI incidence is identified, the more contained can be the MI expansion and its effect on LV contractility and function, leading to better and more improved survival rate [5]. Therefore, growing prevalence of MI and mortality has gained importance worldwide to the research and development of techniques for mass screening to deliver prognostic healthcare.

1.2. ECG wave pattern in normal and infarcted heart

Electrocardiogram (ECG) is a noninvasive procedure for obtaining the electrical activity of the heart over time using 12 surface electrodes (leads). The evaluation of alterations in the cardiac electrical activity using 12 lead ECG is normally used to diagnose and evaluate the risk of MI development. Together with patient history and clinical findings, the 12-lead ECG is still the most readily available and best method for the early diagnosis of MI [6–9]. In addition to the detection of MI, the 12 leads can be used to specify the region of myocardial damage. By their position, the 12 ECG leads can be used to distinguish MI occurring in different regions of the heart, such as inferior, lateral, anterior and posterior; combinations of these such as anterolateral and infero-posterior infarction. The 12 leads cluster around the heart and limbs in the horizontal plane and provide electrical activity views of the heart: (i) from anterior (front) using V_1 to V_4, (ii) from left (lateral) using V_5 to V_6, lead I and aVL, and (iii) from inferior using leads II, III, and aVF [10,11].

The electrical current flows from high potential (positive) to low potential (negative) in a normal healthy heart. If the electrical or contractile function of the heart is interrupted for some reason, the flow of electric signals throughout the myocardium will also be affected. For example, in MI condition the flow of electrical signal through infarcted zone gets affected due to the death of tissue in that part of the heart muscle. So when the electrical wave pattern is disrupted by an infarct, the ECG recording will indicate the abnormal flow of current. Within an infarcted heart, the electrical current flows opposite to the expected direction of flow, resulting in elevated or depressed ST segment. These signs of ST elevation or depression for anterior-septal infarction are seen in V_1 to V_4, for posterior infarction in V_1 and V_2, for inferior infarction in leads II, III and aVF, and for lateral in V_5, V_6, I, and aVL [12].

1.3. Detection of MIs by automated analysis of ECG signal pattern

Although ST segment elevation or depression can be seen on the ECG signals, it is the combined 12 leads ECG signals precise measurement that can indicate exactly where the infarct is located [10,11]. Manual identification of these changes occurring in the 12 leads and diagnosis of MI mainly for huge dataset can be difficult, time consuming and may even result to incorrect differentiation of the normal and abnormal ECG signals. This hurdle can be overcome by employing computer-aided automated diagnostic system. The computer-aided-based systems can enhance the diagnosis accuracy by determining minute variations in the ECG signal [13]. Various computational algorithms and systems have been developed for the 12 lead ECG signal analysis, and its automated processing to detect and locate MI. A summary of research work done using 12 lead ECG signal in the detection and localization of MI is provided in Table 7.

In a study with ECG signal, QRS measurements obtained using the leads V_2 to V_4 combined with neural networks is shown to be able to localize anterior infarction with accuracy of 79% and specificity of 97% [14]. In addition, QRS complex characterization using discrete wavelet transform (DWT) are able to differentiate normal, inferior MI, and anterior MI with receiver operating characteristics (ROC) discrimination power of about 75% [15]. A set of time-domain features, such as QRS amplitude and duration, T amplitude and Q/R ratio extracted from each of the 12 leads are capable of localizing inferior MI and anterior MI with specificity of 92.73% and 93.33% by using fuzzy multi-layer perception (FMLP) network [16]. It is evident that identification of the anatomic location of threatening MIs is important in order to estimate the amount of jeopardized myocardium and to determine the relative risk of morbidity and mortality. However, extraction and analysis of the time-domain features does not provide a good depiction of the nonlinear and nonstationary ECG signal data in the localization of MI. Hence, there is a requirement for the transformation of data from time domain to frequency domain, by using which concealed information can be extracted significantly [17]. The nonlinear features can help to decipher the hidden complexities in the ECG signals.

Our present work focuses on the extraction of different nonlinear features extracted from 12 ECG leads, which are efficient in identifying the subtle changes within signal for the detection and localization of 10 types of MIs. The block diagram of the proposed method is shown in Fig. 1. Each ECG signal is subjected to four levels of DWT decomposition. Later, 12 types of nonlinear features (approximate entropy (E_a^x), signal energy (Ω^x), fuzzy entropy (E_f^x), Kolmogorov–Sinai entropy (E_{ks}^x), permutation entropy (E_p^x), Renyi Entropy (E_r^x), Shannon entropy (E_{sh}^x), Tsallis entropy (E_{ts}^x), wavelet entropy (E_w^x), fractal dimension (F_D^x), Kolmogorov complexity (C_k^x), and largest Lyapunov exponent (E_{LLE}^x)) are extracted from DWT coefficients. Then, the significant features obtained using t-test and ANOVA are ranked based on their t-values and F-values, and used for classification using k-nearest neighbours (KNN) classifier.

2. Material used

The 12 lead ECG signals required for the study are obtained from Physiobank (PTB Diagnostic ECG database) open access database [18]. We have downloaded a total of 52 normal subjects and 148 MI patients' 12 lead ECG recorded signals. The 148 MI patients' ECG signals are identified to have 10 types of different infarctions, such as anterior, anterior lateral (anterolateral), anterior septal (anteroseptal), inferior, inferior lateral (inferolateral), inferior posterior (inferoposterior), inferior posterior lateral (inferoposterolateral), lateral, posterior, and posterior lateral (posterolateral).

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