Machine Learning Improves the Detection of Misplaced V1 and V2 Electrodes During 12-Lead Electrocardiogram Acquisition

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Abstract

Electrode misplacement during 12-lead Electrocardiogram (ECG) acquisition can adversely cause false ECG interpretation, diagnosis and subsequent incorrect clinical treatment or lack thereof. A common misplacement errors are the. superior placement of V1 and V2 electrodes. The analysis of ECG signals that were recorded from ECGs with vertically misplaced leads V1 and V2 can yield a false diagnosis of Brugada syndrome, myocardial infarction (MI) or left ventricular hypertrophy (LVH). The aim of the current research was to detect lead V1 and V2 misplacement using feature engineered machine learning algorithms to enhance ECG data quality to improve clinical decision making in cardiac care. In this particular study, we reasonably assume that V1 and V2 are concurrently superiorly misplaced together. ECGs for 450 patients, (normal n=150, LVH n=150, MI n=150) were extracted from body surface potential maps. ECG signals were extracted using correct and incorrectly placed V1 and V2 electrodes, i.e. leads derived from the fourth intercostal space (ICS) as well as the first ICS, second ICS, and third ICS. The prevalence for correct and incorrect leads were 50%. Sixteen features were extracted including: morphological, statistical and time-frequency features. Two feature selection approaches (filter method and wrapper method) were applied to find an optimal set of features that provide a high accuracy when used with a machine learning model. To ensure accuracy, six classifiers were applied including: fine tree, coarse tree, bagged tree, Linear Support Vector Machine (LSVM), Quadratic Support Vector Machine (QSVM) and logistic regression. The accuracy of V1 and V2 misplacement detection was 94.3% in the first ICS, 92.7% in the second ICS and 70% in third ICS respectively. Based on accuracy results, bagged tree was the best classifier in the first, second and third ICS to detect V1 and V2 misplacement

1. Introduction

The standard 12-lead ECG is the most commonly used layout to record the electrical activity of the heart muscle. However, the ECG has a low sensitivity (30–70 %) and specificity (70–95 %) to detect acute coronary syndromes for many reasons. An electrode misplacement which could arise from challenging for clinicians need to keep the chest wall clear for other diagnostic procedures [1][2][3]. Misplacement effects on the 12-lead ECG can cause differences in ECG morphology and interpretation [4]. Recorded ECGs with lead misplacements can result in significant false diagnoses made by computer-based systems or human interpretation or such a false diagnosis of ventricular hypertrophy, anterior infarction, ischemia, or Brugada syndrome which could lead to a false diagnosis in 17–24 % of patients [5]. Lead V2 is the most sensitive signal to electrode misplacement followed by V3, V1 and V4, while in leads V5 and V6 there are no apparent changes in ECG morphology [2]. Body surface potential maps (BSPMs) were used for simulating the electrode misplacement in 12-lead ECG [6]. The P-wave morphology changes in V1 and V2 were significant at 2 cm distances, while other leads were not prominently different up to 5 cm from the location of V3, V4, V5 and V6. V1 is more sensitive to vertical misplacements than to horizontal misplacements compared to other leads. Misplacement can conceal myocardial infarction or even mimic a lateral MI in a true case of inferior MI [7][8]. V1 and V2 misplacement too high or too low can cause misplacement of the other precordial electrodes, which can cause false diagnoses of left ventricular hypertrophy

[9] [10]. An electrode misplacement simulator (EMS) which is a web-based simulation tool for training students was suggested to improve electrode placement. The cardio quick patch (CQP) device was developed to help clinicians in accurately placing precordial electrodes during ECG recording [11][12]. CQP significantly improved the positioning accuracy of precordial electrodes V1, V3–V6 with little additional effort [12]. A selection method has been developed to detect the optimal placement of bipolar electrodes. However, the performed study suggested further investigations to assess if abnormal atrial activation can affect the performance of the P-lead [6].

2. Method

2.1. Data collection

The signals for V1 and V2 leads were extracted from a body surface potential maps (BSPMs) which is comprised of 117 nodes (leads) and is known as the Kornreich dataset [13][14][15]. The Kornreich dataset has been used in a large number of studies around the world, but no study has used it to detect V1 and V2 misplacement. The ECG dataset comprises three different subject types including ECGs of MI, LVH and normal subjects. This research has ECGs for 450 subjects, (normal n=150, LVH n=150, MI n=150). For each subject, the ECG signals were recoded simultaneously for leads V1 and V2. For each BSPM, the correct ECG and an incorrect ECG (where leads V1 and V2 were misplaced) were extracted. To provide a class balance, 50% of cases are correct ECGs and 50% are incorrect. For pre-processing, a transformation matrix has been multiplied with 117 nodes in each BSPM to get 352 nodes that provide a greater resolution (using the Dalhousie torso [13]). Nodes 169 and 171 are denoted in the green color as shown in figure 1 to represent V1 and V2 leads in their correct positions. Nodes 126 and 128 are denoted in the blue color to represent V1 and V2 misplacement in the third ICS and nodes 83 and 85 represent the misplaced V1 and V2 leads in the second ICS.

2.2. Feature extraction

Sixteen ECG features have been extracted in three different domains including time domain features such as P wave amplitude, PR interval, QRS onset value, R amplitude, offset of the QRS and S amplitude and Statistical features including the mean, standard deviation, skewness, kurtosis of the ECG, Pearson correlation coefficient and the root mean square error (RMSE) between V1 and V2 leads because they are commonly misplaced together. Time-frequency features are derived using a discrete wavelet transform (DWT) using 4 levels and symlets wavelet mother function. The maximum, minimum and mean value of details coefficient four(D4) was considered as features.

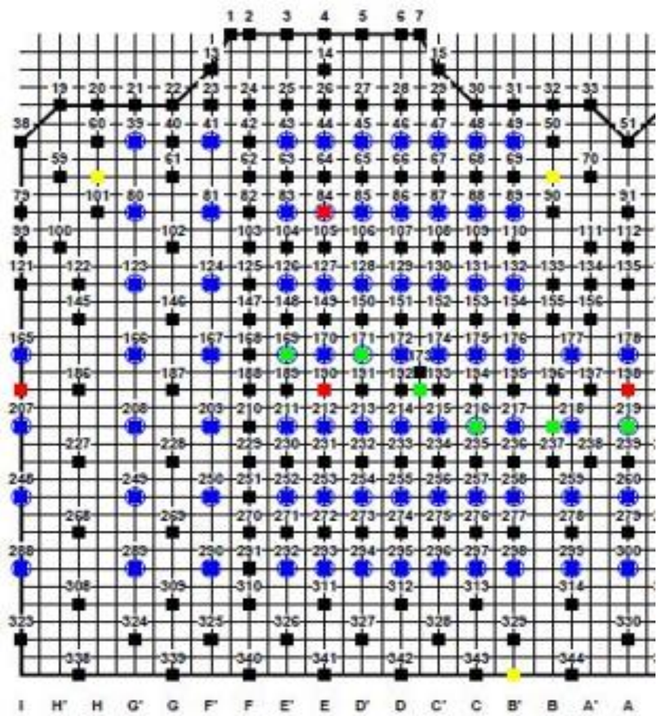


Figure 1. Dalhousie torso with 352 nodes.

2.3. Feature selection

To find an optimal set of features that provides a good classification results; A hybrid feature selection approach (combining the filter method and the wrapper method) has been applied. The sixteen features have been ranked using five different filter methods including, mutual information feature selection (MIFS) in equation (1), joint mutual information JMI in equation (1), Entropy in equation (2) and maximum relevance minimum redundancy (MRMR) in equation (1), and Relief in equation (3). Then, a backwards elimination algorithm has been applied on ranked features to find an optimal set of features.

$$f_t = \arg\max \mathrm{I}(x_i; y) - \left[\alpha \sum_{k=1}^{t-1} I\left(x_{fk}; x_i\right) - \beta \sum_{k=1}^{t-1} I\left(x_{fk}; x_i | y\right)\right] \quad (1)$$

Where x represents features and y represents labels

In JMI: $\alpha = \frac{1}{t-1}$ and $\beta = \frac{1}{t-1}$

In MIFS: $\alpha = 0$ and $\beta = 0$

In MRMR: $\alpha = \frac{1}{t-1}$ and $\beta = 0$

$$H(X) = -\sum p(x) \log_2 p(x) \quad (2)$$

where x represents features

$$W_i = W_i - (x_i - nearHit_i)^2 + (x_i - nearMiss_i)^2 \quad (3)$$

w is the weighted vector initialised with zeros, where x represents features, nearHit is the closest same class instance and nearMiss is the closest different class instance.

2.4. Classification

Six classifiers including 1) fine tree, 2) coarse tree, 3) bagged tree, 4) Linear Support Vector Machine (LSVM), 5) Quadratic Support Vector Machine (QSVM) and 6) logistic regression have been applied to get the best possible accuracy.

3. Results

The six machine learning classifiers were tested on each feature selection algorithm to attain the best performance. Bagged tree classifier got the highest accuracy among the other classifiers as shown in table 1.

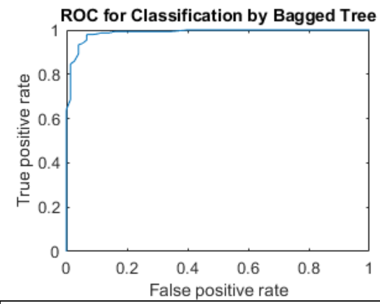
Table 1. Machine learning classifiers accuracy.

			1st Intercostal Space		
	ENTR	**JMI**	**MIFS**	**MRMR**	**REL**
FTREE	87%	88.3%	87.0%	87.0%	87.7%
CTREE	87.7%	87.7%	87.7%	87.7%	87.7%
LOG	87.7%	85.7%	87.7%	87.7%	87.7%
LSVM	84.7%	84.3%	84.7%	84.7%	85.0%
QSVM	87.3%	91.0%	87.3%	87.3%	88.0%
BAGT	**94.3%**	93.7%	92.0%	91.7%	93.3%
			2nd Intercostal Space		
FTREE	85.0%	85.0%	85.0%	82.7%	84.0%
CTREE	87.7%	87.7%	87.7%	85.7%	87.7%
LOG	82.7%	82.7%	83.7%	81.3%	82.7%
LSVM	78.7%	78.7%	75.7%	76.0%	78.7%
QSVM	79.0%	79.0%	78.3%	79.0%	79.0%
BAGT	88.3%	92.3%	90.3%	**92.7%**	90.7%
			3rd Intercostal Space		
FTREE	60.0%	59.0%	60.3%	58.3%	59.0%
CTREE	69.7%	69.7%	69.7%	69.7%	69.7%
LOG	64.3%	63.7%	65.7%	63.7%	63.7%
LSVM	59.0%	60.3%	61.0%	61.3%	60.3%
QSVM	58.7%	60.0%	62.7%	60.3%	60.0%
BAGT	69.3%	**70.0%**	66.3%	69.0%	**70.0%**

FTREE: fine tree, **CTREE:** coarse tree, **LOG:** logistic regression, **LSVM:** linear support vector machine, **QSVM:** Quadratic Support Vector and **BAGT:** bagged tree. **ENTR:** entropy, **JMI:** joint mutual information, **MIFS:** mutual information feature selection, **MRMR:** maximum relevance minimum redundancy and **REL:** relief

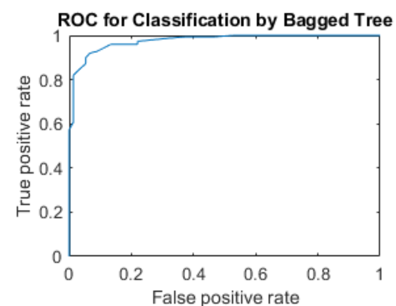
Sensitivity and specificity were calculated in each IC space for the best classifier. Figure 2.a shows ROC curve for bagged tree in the first ICS, figure 2.b shows ROC curve in the second ICS and figure 2.c shows ROC curve in the second ICS. The best feature selection algorithm in the first ICS was entropy, while the best feature selection algorithm in the second ICS was MRMR and in the third ICS the best feature selection was JMI and relief algorithm.

a.



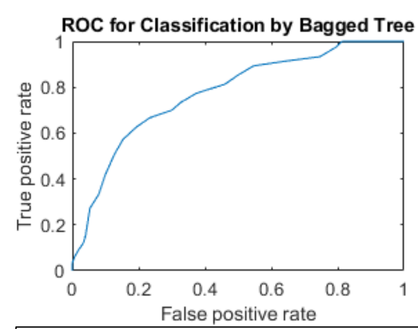
Prevalence: 50.0%
Sensitivity: 94.0%
Specificity:94.6%, Accuracy: 94.3%
Predictivity of positive test: 94.7%
Predictivity of negative test:94.0%
F1-score: 0.9

b.



Prevalence: 50.0%
Sensitivity: 93.3%
Specificity:92.0%, Accuracy:92.7%
Predictivity of positive test: 92.1%
Predictivity of negative test 93.2%
F1-score: 0.9

c.



Prevalence: 50.0%
Sensitivity: 70.0%
Specificity:70.0%, Accuracy: 70.0%
Predictivity of positive test: 70.0%
Predictivity of negative test:70.0%
F1-score: 0.7

Figure 2. Roc curve for bagged tree in each ICS.

4. Discussion

This study presents a machine learning algorithm to detect V1 and V2 lead misplacement. The aim of this work is to improve ECG signal quality which can help clinicians in decision making in cardiac care. According to the literature review, ECG lead misplacement is one of the most critical issues affecting ECG morphology and interpretation as well [8]; which can cause false diagnoses and inappropriate treatment. V1 and V2 are commonly misplaced leads and they placed too high and wide from their correct position which can cause a false diagnosis. This study highlights a noticeable decline in accuracy when there is lead misplacement in the third ICS. Which is expected; because the ECG features will be more similar to features recorded in the 4th ICS. This suggests future research to improve accuracy of detecting chest lead misplacement in the third ICS using a new method.

5. Conclusion

In this study, bagged tree provides the best performance for detecting chest electrode misplacement in three ICSs (1^{st}, 2^{nd}, 3^{rd}). Based on feature selection algorithm, in the first ICS the best feature selection algorithm was entropy, while in the second ICS, the best algorithm was MRMR and in the third ICS the best feature selection was JMI and relief. Based on results, another study should be carried to improve performance in the third ICS by using new features or including a new machine learning classifier. A broader dataset should be used in a derivation study to check if the developed algorithm can improve ECG data quality and decision making in cardiac care

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References

[1] M. Kania et al. The Effect of Precordial Lead Displacement on P-wave Morphology in Body Surface Potential Mapping. Computing in Cardiology 2013. Vol.40, pp.531-534, 2013.

[2] M. Kania et al. The effect of precordial lead displacement on ECG morphology. Med Biol Eng Comput. Vol.52, pp.109–119, 2014.

[3] I. lekova. et al. Detection of Electrode Interchange in Right Precordial and Posterior ECG Leads. Computing in Cardiology 2015. Vol.42, pp.1149-1152, 2015.

[4] R. Andrés. et al. Main artifacts in electrocardiography. Ann Noninvasive Electrocardiol. Vol.23, pp.1-8, 2018.

[5] R. Bond et al. The effects of electrode misplacement on clinicians' interpretation of the standard 12-lead electrocardiogram. European Journal of Internal Medicine. Vol. 23, pp.610–615, 2012.

[6] A. Kennedy et al. Detecting the Elusive P-Wave: A New ECG Lead to Improve the Recording of Atrial Activity. IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, Vol.63, pp.243-249, 2016

[7] A. Rudiger et al. Influence of Electrode Misplacement on the Electrocardiographic Signs of Inferior Myocardial Ischemia. AMERICAN JOURNAL OF EMERGENCY MEDICINE. Vol.21, pp.574-577, 2003.

[8] W. Andrew et al. A computer-human interaction model to improve the diagnostic accuracy and clinical decision-making during 12-lead electrocardiogram interpretation. Journal of Biomedical Informatics Vol.64, pp.93–107,2016.

[9] B. Walsh. et al. Misplacing V1 and V2 can have clinical consequences. American Journal of Emergency Medicine. Vol.36, pp.865–870, 2018.

[10] E. Soliman. A simple measure to control for variations in chest electrodes placement in serial electrocardiogram recordings. Journal of Electrocardiology. Vol.41, pp.378–379, 2008.

[11] R. Bond et al. A simulation tool for visualizing and studying the effects of electrode misplacement on the 12-lead electrocardiogram. Journal of Electrocardiology. Vol.44, pp.439–444, 2011.

[12] R. Bond et al. Human factors analysis of the CardioQuick Patch®: A novel engineering solution to the problem of electrode misplacement during 12-lead electrocardiogram acquisition. Journal of Electrocardiology. Vol.49, pp.911–918, 2016.

[13] F. Kornreich, Montague TJ, Rautaharju PM. Identification of first acute Q wave and non-Q wave myocardial infarction by multivariate analysis of body surface potential maps. Circulation. 1991 Dec;84(6):2442-53.

[14] T. Montague, Smith ER, Cameron DA, Rautaharju PM, Klassen GA, Felmington CS, Horacek BM. Isointegral analysis of body surface maps: surface distribution and temporal variability in normal subjects. Circulation. 1981 May;63(5):1166-72.

[15] F. Kornreich, Lux RL, MacLeod RS. Map representation and diagnostic performance of the standard 12-lead ECG. Journal of electrocardiology. 1995 Jan 1;28:121-3

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