

Role of the Historical Electrocardiogram in Identifying Acute Coronary Syndrome

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Abstract

Sensitivity (SE) and specificity (SP) for diagnosing acute coronary syndrome in prehospital ECGs is insufficient. The guidelines state that comparison of prehospital ECGs and a previous ECG tracing is valuable, particularly in case of pre-existing ECG abnormalities. Our study investigates the additional value of the historical ECG in detecting ischemia in prehospital phase. Data belong to the SUBTRACT study, which includes couples of 10-second 12-lead prehospital and historical ECGs from 1182 patients. Retrospective evaluation of the prehospital ECGs yielded 169 patients with, and 1013 patients without ischemia in prehospital ECG. Overall, each ECG couple were characterized by 47 features, which were grouped in the first set, including 18 direct measurements from the prehospital ECG, and the second set, including the first set and 29 serial prehospital-historical ECG differences. The sets were used to create two dendrograms, that divided the data into two clusters. Clusters were labeled as ischemia cluster (i.e., including over 50% of the ischemia patients) and non-ischemia cluster, and evaluated by SE and SP. Metrics of the second dendrogram (SE=71%; SP=69%) are higher than those of the first dendrogram (SE=22%; SP=57%). We conclude that serial differences improve ischemia identification in the ambulance, thus proving the additional diagnostic value of a historical ECG.

1. Introduction

Acute Coronary Syndrome (ACS) includes myocardial infarction and unstable angina [1]. Electrocardiograms (ECGs) performed in the prehospital setting have an essential role in the early detection of ACS and in guiding critical decisions, such as the urgent transfer of the patient to specialized cardiac care facilities [4] in which emergency and cardiology teams can already prepare for immediate intervention even during the ambulance ride to the hospital [2], [3].

Despite their importance, the diagnostic performance of prehospital ECGs in identifying ACS among the typical patient mix (patients presenting to the emergency medical

services with non-traumatic chest pain in rest) is insufficient, particularly in terms of sensitivity and specificity [5]. By considering the results reported in the literature, sensitivity is about 60-80%, while specificity is 70-90% [3], but the studies that investigated this diagnostic performance focused only on detection of STEMI ACS.

The challenge in diagnosing ACS with prehospital ECGs is aggravated in patients with pre-existing ECG abnormalities. Conditions such as left bundle branch block, ventricular hypertrophy, or previous myocardial infarction can jeopardize the ECG signs of ACS, leading to diagnostic uncertainty and potential delays in treatment [6]. Current clinical guidelines suggest for the comparison of prehospital ECGs with previous ECG tracings [7]. However, the practical implementation of comparing prehospital ECGs with historical ECG records presents several logistical challenges. In many emergencies medical systems, it is difficult to timely access a previous ECG of a patient, due to the lack of integrated health information systems and the nature of emergency situations [8]. Consequently, the potential diagnostic benefit of including historical ECG into the prehospital assessment of ACS has not been investigated.

Thus, the aim of this study is to evaluate the additional diagnostic value of using the most recent historical ECG in the prehospital identification of ischemia.

2. Materials and Methods

2.1. Data

Data belong to the SUBTRACT study, initiated by the Amsterdam Medical Center (AMC) and the Leiden University Medical Center (LUMC), in which a number of regional hospitals and two emergency medical services participated. The SUBTRACT study was a retrospective observational study that aimed to evaluate the diagnostic value of serial electrocardiography for the detection of myocardial ischemia in the prehospital phase [9], [10] in 1425 patients who were urgently transported by ambulance to any of the participating hospitals because of non-traumatic chest pain.

For each patient, two 10-second 12-lead ECGs were

considered: an ECG made in the ambulance (AECG) for ruling in/out myocardial ischemia, and an earlier made elective historical ECG that served as a reference (HECG). AECGs were recorded with LIFEPAK 12 (Physio-Control), using the Mason-Likar electrode configuration (extremity electrodes on the thorax). HECGs were retrieved by searching the ECG databases of any of the participating hospitals; hence, HECGs were not necessarily made in the same hospital in which the non-traumatic chest pain patient was admitted after the ambulance ride. The HECGs retrieved in the various participating hospitals were recorded by different electrocardiographs (GE, Schiller, Mortara, Siemens/Dräger); all were recorded with the standard electrode configuration (extremity electrodes on wrists and ankles).

When discharged from the hospital, the clinical data demonstrated that 231 patients had ACS [10]. The presence or absence of myocardial ischemia in all AECGs was retrospectively assessed by extrapolating back in time the clinical data obtained during hospital admission of the patient after the ambulance ride [11]. Each ACG was adjudicated on a 5-point scale, ranging from likely ischemic, probably ischemic, uncertain, probably non-ischemic and likely non-ischemic. In the current study, patients classified as likely ischemic and likely non-ischemic were considered as cases (169 patients) and controls (1013 patients), respectively.

Ischemia and ACS are not fully overlapping. E.g., patients with stable angina can have an ischemic ECG but have no ACS, while patients with unstable angina have ACS but have episodes with and episodes without ischemia. Our study focuses on ischemia detection.

2.2. Feature Extraction

For each subject, 47 features were computed: 18 direct measurements computed in the AECG (Table 1), and 29 serial ECG features computed by subtracting the HECG to the AECG feature (Table 2).

2.3. Clustering Algorithm

The features extracted from the cases and controls were used to create a dendrogram for data clustering, a machine learning tool that does not consider the clinical evaluation of the patients. A dendrogram is a diagram used in hierarchical clustering to illustrate the arrangement of the clusters produced by the clustering algorithm. It's a tree-like structure that represents the nested clusters formed by grouping similar data points together [12], [13]. Dendrograms are useful for visualizing the hierarchical structure of clusters and for understanding how the data points are grouped together based on their similarity or dissimilarity. They can help in determining the appropriate

number of clusters to use and in interpreting the relationships between the clusters and the individual data. Specifically, two dendrograms were created: dendrogram 1 is created by uniquely using the direct measurements and dendrogram 2 is created by using all features.

2.4. Statistical Analysis

Each dendrogram discriminated patients into two clusters (C1 and C2), successively labelled as ischemia cluster (i.e. including over 50% of the patients with an ischemic AECG) and non-ischemia cluster. Sensitivity (SE) and specificity (SP) were used to evaluate goodness of clustering. The patients inside the clusters were characterized in terms of numbers of cases and numbers of controls.

3. Results

Figure 1 shows dendrogram 1 and 2 in panels A and B, respectively. For each dendrogram, data are groups into two clusters, C1 (blue) and C2 (red). Table 3 lists the numbers of the subjects present in each of the clusters, together with the number of cases and controls according to the clinical evaluation of the patients. Clusters obtained using the second set of features yielded higher values of SE (71%) and SP (69%) than those obtained using the first set of features (SE = 22%; SP = 57%).

Table 1. List of direct measurements computed from AECG.

#	Acronym	Description
1	QRS (ms)	QRS duration
2	MQRS (μ V)	maximal QRS vector magnitude
3	IQRS (mV·ms)	QRS-integral vector magnitude
4	QRSC (%)	QRS complexity
5	J (μ V)	J-point vector magnitude
6	SJ8 (μ V)	summed absolute J-point amplitudes of independent leads
7	SJ12 (μ V)	summed absolute J-point amplitudes of all leads
8	MT (μ V)	maximal T vector magnitude
9	IT (mV·ms)	T-integral vector magnitude
10	TC (%)	T-wave complexity
11	TS (%)	T-wave symmetry
12	NPT (adi)	Lead number with positive T waves
13	QT (ms)	QT interval
14	VG (μ V)	ventricular gradient magnitude
15	SA ($^\circ$)	QRS-T spatial angle
16	HR (bpm)	heart rate
17	Age	Age
18	Sex	Sex

Table 2. List of serial ECG features computed from AECG and HECG.

#	Acronym	Description
19	QRSD (ms)	QRS duration difference
20	QRSaD (ms)	QRS duration absolute difference
21	MQRSD (μV)	maximal QRS vector magnitude difference
22	MQRSaD (μV)	absolute value of maximal QRS vector magnitude difference
23	IQRSD ($\text{mV}\cdot\text{ms}$)	QRS-integral vector magnitude difference
24	IQRSaD ($\text{mV}\cdot\text{ms}$)	absolute value of QRS-integral vector magnitude difference
25	QRSCD (%)	QRS complexity difference
26	QRSCaD (%)	absolute value of QRS complexity difference
27	JD (μV)	J-point vector magnitude difference
28	SDJ8 (μV)	summed absolute J-point amplitudes difference of independent leads
29	SDJ12 (μV)	summed absolute J-point amplitudes difference of all leads
30	MTD (μV)	maximal T vector magnitude difference
31	MTaD (μV)	absolute value of maximal T vector magnitude difference
32	ITD ($\text{mV}\cdot\text{ms}$)	T-integral vector magnitude difference
33	ITaD ($\text{mV}\cdot\text{ms}$)	absolute value of T-integral vector magnitude difference
34	TCD (%)	T-wave complexity difference
35	TCaD (%)	absolute value of T-wave complexity difference
36	TSD (%)	T-wave symmetry difference
37	TSaD (%)	absolute value of T-wave symmetry difference
38	NPTD (adi)	difference between Lead number with positive T waves
39	NTPC (adi)	number of leads that change T-wave polarity
40	QTD (ms)	QT-interval difference
41	QTaD (ms)	absolute value of QT-interval difference
42	VGD (μV)	ventricular gradient magnitude difference
43	SAD ($^\circ$)	QRS-T spatial angle difference
44	SAaD ($^\circ$)	absolute value of QRS-T spatial angle difference
45	HRD (bpm)	Heart rate difference
46	HRaD (bpm)	absolute value of heart rate difference
47	AgeD	Age of the HECG

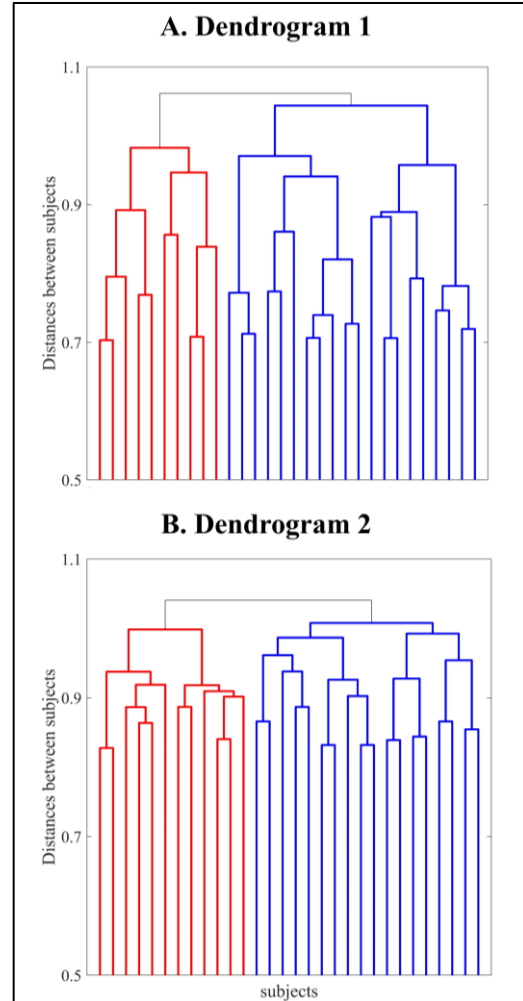


Figure 1. Dendrograms with clusters C1 (blue) and C2 (red). Dendrogram 1 is created by using the direct measurements. Dendrogram 2 is created by using all features.

Table 3. Numbers of subjects in each of the clusters of the dendrograms, with the number of cases and controls.

		Cases	Controls
Dendrogram 1	C1	296	72
	C2	886	97
Dendrogram 2	C1	775	53
	C2	407	116

4. Discussion

This study investigated the additional diagnostic value of incorporating historical ECGs into the prehospital detection of ischemia. The results demonstrate a significant improvement in both SE and SP when historical ECGs are included in the diagnostic process. Specifically, the dendrogram based on both prehospital ECG direct

measurements and serial historical differences achieved SE and SP equal to 71% and 69%, respectively, compared to the much lower values of 22% and 57% for SE and SP when using only prehospital direct measurements. This increase in diagnostic performance underscores the value of a historical ECG in detecting ischemia in a prehospital ECG, important in case of pre-existing ECG abnormalities.

Although ischemia and ACS do not completely overlap, the enhanced SE and SP mean that more ACS are correctly identified prehospital, allowing for timely intervention and potentially better patient outcomes, while reducing false positives, unnecessary hospital admissions, and unwarranted treatments. Early and accurate diagnosis of ACS in the prehospital setting is crucial as it facilitates immediate clinical assessment and the administration of life-saving treatments (e.g., direct transfer to a cardiac catheterization laboratory), thereby reducing myocardial damage and improving survival rates. Moreover, prehospital ECGs guide critical decisions like the urgent transfer of patients to specialized cardiac care facilities, ensuring that the hospital emergency/cardiology teams are prepared for immediate intervention.

However, several practical challenges must be addressed for widespread implementation. One of the main issues is the timely availability of historical ECG during emergencies. Many emergency medical services lack integrated electronic health records that can provide immediate access to previous ECGs. Developing more robust and interconnected systems is crucial to solve it. Additionally, accurate patient identification and linking them to their historical ECGs can be difficult. Further research is needed to validate these findings in larger and more diverse populations and to explore the impact of using historical ECGs on clinical outcomes such as time to treatment, mortality rates, and long-term health consequences. Investigating the integration of artificial intelligence and machine learning algorithms to assist in the real-time comparison of prehospital and historical ECGs could enhance diagnostic accuracy.

5. Conclusion

Inclusion of differential measurements, improves identification of ACS in ambulances, indicating that historical ECG provides additional diagnostic value with respect to prehospital ECG only.

References

- [1] D. L. Bhatt, R. D. Lopes, and R. A. Harrington, "Diagnosis and treatment of acute coronary syndromes: a review," *JAMA*, vol. 327, no. 7, pp. 662–675, Feb 2022.
- [2] E. A. Amsterdam et al., "2014 AHA/ACC guideline for the management of patients with non-ST-elevation acute coronary syndromes: a report of the American College of Cardiology/American Heart Association Task Force on

- Practice Guidelines," *J Am Coll Cardiol*, vol. 64, no. 24, pp. e139–e228, Dec 2014.
- [3] S.S. Virani et al., "2023 AHA/ACC/ACCP/ASPC/NLA/PCNA Guideline for the Management of Patients With Chronic Coronary Disease: A Report of the American Heart Association/American College of Cardiology Joint Committee on Clinical Practice Guidelines," *Circulation*, vol. 148, no. 9, pp. e9–e119, Aug 2023.
- [4] H. H. Ting et al., "Implementation and integration of prehospital ECGs into systems of care for acute coronary syndrome: a scientific statement from the American Heart Association Interdisciplinary Council on Quality of Care and Outcomes Research, Emergency Cardiovascular Care Committee, Council on Cardiovascular Nursing, and Council on Clinical Cardiology," *Circulation*, vol. 118, no. 10, pp. 1066–1079, Sep 2008.
- [5] C. A. Swenne, and C. C. ter Haar, "Context-independent identification of myocardial ischemia in the prehospital ECG of chest pain patients", *J Electrocardiol*, vol. 82, pp. 34–41, Jan-Feb 2024.
- [6] E. B. Sgarbossa et al., "Electrocardiographic diagnosis of evolving acute myocardial infarction in the presence of left bundle-branch block," *New England Journal of Medicine*, vol. 334, no. 8, pp. 481–487, Feb 1996.
- [7] E. M. Antman et al., "ACC/AHA guidelines for the management of patients with ST-elevation myocardial infarction: a report of the American College of Cardiology/American Heart Association Task Force on Practice Guidelines," *J Am Coll Cardiol*, vol. 44, no. 3, pp. E1–E211, Aug 2004.
- [8] J. K. Z. Hemsey and B. J. Drew, "Prehospital electrocardiography: a review of the literature," *J Emerg Nurs*, vol. 38, no. 1, pp. 9–14, Jan 2012.
- [9] A. Sbröllini, C. C. Ter Haar, C. Leoni, M. Morettini, L. Burattini, and C. A. Swenne, "Advanced repeated structuring and learning procedure to detect acute myocardial ischemia in serial 12-lead ECGs," *Physiol Meas*, vol. 44, no. 8, Aug 2023.
- [10] C. C. Ter Haar et al., "An initial exploration of subtraction electrocardiography to detect myocardial ischemia in the prehospital setting," *Annals of Noninvasive Electrocardiology*, vol. 25, no. 3, May 2020.
- [11] C. C. Ter Haar, and C. A. Swenne, "Post hoc labeling an acute ECG as ischemic or non-ischemic based on clinical data: A necessary challenge." *J Electrocardiol*, vol. 81, pp. 75–79, Nov-Dec 2020.
- [12] C. Lopez, S. Tucker, T. Salameh, and C. Tucker, "An unsupervised machine learning method for discovering patient clusters based on genetic signatures," *J Biomed Inform*, vol. 85, pp. 30–39, Sep 2018.
- [13] G. Papin et al., "Clinical and biological clusters of sepsis patients using hierarchical clustering," *PLoS One*, vol. 16, no. 8, Aug 2021.

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