On the Estimation Performance of Patient-Specific Linear ECG-Lead Transformations in the Presence of Cardiac Conduction Changes

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Abstract

Linear ECG-lead transformations (LELTs) are used to estimate unrecorded target leads from a number of recorded basis leads. Population (POP) based LELTs are developed using data from multiple subjects, while patient-specific (PS) LELTs are developed using data of a single subject. The estimation performance of PS LELTs has been reported to be superior to what is achieved using POP based LELTs. However, PS LELTs are often developed and assessed on ECGs that belong to the same diagnostic class.

Our research aimed to compare the estimation performance of PS and POP based LELTs. This comparison was conducted in a scenario where the diagnostic class of the ECGs associated with a subject changes after development but before the performance assessment of the PS LELTs. The comparison was performed for PS and POP based LELTs that estimate target leads V1, V3, V4 and V6 from basis leads I, II, V2 and V5. Root mean square error values calculated between derived and recorded target leads were used for the quantification of the estimation performance.

Our findings indicate that a change in the diagnostic class, which occurs after the development of PS LELTs, can reduce the estimation performance of these LELTs to a level comparable to that achieved by POP based LELTs.

1. Introduction

Linear ECG lead transformations (LELTs) are a well-established concept in computerized electrocardiography. They are used to estimate unrecorded target leads from a number of recorded basis leads. This estimation is performed by applying the basis leads to a LELT matrix [1, 2]. Application areas of LELTs include the estimation of ECG leads that are not commonly recorded in clinical practice [1] or reduced lead systems [2]. Reduced lead systems aim to estimate unrecorded leads of the 12-lead ECG or the Frank VCG [3] from a reduced number of monitoring compatible electrodes. LELT matrices are commonly developed using training sets and multivariate linear regression analysis [4]. Two approaches for the development of LELT matrices exist. The first approach leads to population (POP) based LELTs [5]. These matrices are developed using ECG data from multiple subjects and are intended to be used with ECG data from different previously unseen subjects. The second approach leads to patient-specific (PS) LELTs [5]. These matrices are developed using data of a single subject and are intended to be used with ECG data of this subject only. The estimation performance of PS LELTs has been reported to be superior to what is achieved using POP based LELTs.

Recent work [4] has demonstrated that POP based LELTs that are developed using ECGs of only one diagnostic class can lead to biased LELT matrices. The estimation performance of these biased matrices was found to vary notably across different diagnostic classes. However, PS LELTs are often developed and tested on ECGs that belong to the same diagnostic class. This potentially leads to overly optimistic performance metrics that are been reported in literature.

In this research, we compare the estimation performance of PS and POP based LELTs in the presence of ventricular conduction changes that occur after the development of the PS LELTs. We perform this comparison using LELTs that estimate the target leads V1, V3, V4 and V6 from the basis leads I, II, V2 and V5 of the standard 12-lead ECG.

2. Material and methods

2.1. ECG data

Different standard 12-lead ECG datasets assembled from two sources were used in this research.

Annotations provided in [6] were utilized to identify a cohort of subjects with documented ventricular conduction changes between an initial ECG and a serial ECG. Specifically, subjects were selected based on the

criterion that their initial ECG was classified as normal and their serial ECG was classified as incomplete right bundle branch block (IRBBB). A cohort of 25 subjects was identified using this selection criterion. Two average beats, one of the initial ECG (normal) and one of the serial ECG (IRBBB), were obtained from [7] for each of the 25 subjects. These average beats were generated by the Glasgow ECG program using 10 s of 12-lead ECG data. The QRS-T complexes of the average beats where manually annotated, isolated und used to assemble the datasets $INITwC$ and $SERwC$. Using the annotations in [6], the mean and standard deviation of the time interval between the initial and serial ECGs were quantified as 248 days and 322 days, respectively.

A cohort of subjects without ventricular conduction changes between their initial and serial ECGs was identified using the annotations in [6]. Specifically, subjects were selected based on the criterion that their initial and serial ECGs were classified as IRBBB, and that no new ventricular abnormalities had developed between initial and serial ECGs. Based upon this criterion a cohort of 12 subjects was identified. Using the same methodology employed in the creation of dataset $INITwC$, average QRS-T complexes were generated for both the initial and serial ECGs. The average QRS-T complexes of the initial and the serial ECGs were used to assemble the datasets $INITnoC$ and $SERnoC$ respectively. Mean and standard deviation of the time interval between the initial and the serial ECGs were determined using the annotations in [6] and quantified as 125 days and 169 days, respectively.

Standard 12-lead ECG data of a cohort of 171 subjects (57 normal, 57 left ventricular hypertrophy, 57 old myocardial infarction) was extracted from body surface potential maps (BSPMs). Each BSPM contained electrocardiographic data of 120 BSPM leads. A representative average QRS-T complex was calculated for each of the 120 BSPM leads. Three of the 120 leads were recorded from electrodes placed on the right and left wrist and the left ankle (VR, VL and VF respectively). Electrodes situated at 81 anterior and 36 posterior locations were used to record 117 thoracic leads. A comprehensive description of the recording procedure can be found in [8]. A Laplacian 3D interpolation procedure [9] was applied to the 117 thoracic BSPM leads. This was performed to obtain body surface potentials at the locations of the 352 Dalhousie torso [10] nodes. Body surface potentials from electrode locations that were required but not a direct subset of the 352 Dalhousie torso nodes were obtained using linear interpolation [11]. Average QRS-T complexes of the standard 12-lead ECG were extracted from the interpolated BSPM data. More precisely, body surface potentials on the right wrist, the left wrist, the left ankle and from the location of the six precordial electrodes were used for the determination of the standard 12-lead ECG. This data was used to assemble the dataset $DPOP$.

2.2. Target and basis lead configuration

Our research is performed on LELTs that are developed for a reduced lead system [12] that estimates the target leads V1, V3, V4 and V6 by applying a LELT matrix to the basis leads I, II, V2 and V5 of the 12-lead ECG.

2.3. Development of the LELT matrices

One POP based LELT matrix was developed using the target and basis leads contained in dataset $DPOP$ and the multivariate linear regression approach in (1).

$$_{POP}\boldsymbol{A} = (\,_{POP}\boldsymbol{BL}^{\boldsymbol{T}} \cdot {}_{POP}\boldsymbol{BL}\,)^{-1} \cdot {}_{POP}\boldsymbol{BL}^{\boldsymbol{T}} \cdot {}_{POP}\boldsymbol{TL}\,. \quad (1)$$

Where $[\cdot]^{\boldsymbol{T}}$ and $[\cdot]^{-1}$denote the transpose and the inverse of a matrix respectively, $_{POP}\boldsymbol{A}$ refers to a 4×4 matrix of transformation coefficients that allows for the transformation of the basis leads into the target leads, n refers to the number of sample values of the 171 QRS-T complexes in the dataset $DPOP$, $_{POP}\boldsymbol{TL}$ refers to a $n \times 4$ matrix that contains n sample values of the target leads and $_{POP}\boldsymbol{BL}$ refers to a $n \times 4$ matrix that contains n sample values of the basis leads.

One PS LELT matrix was developed from each average QRS-T complex in the datasets $INITwC$, $INITnoC$, $SERwC$ and S$ERnoC$. This was performed using (2).

$$_{PS}^{i}\boldsymbol{A}_{l} = \left(\,_{PS}^{i}\boldsymbol{BL}_{l}^{T} \cdot {}_{PS}^{i}\boldsymbol{BL}_{l}\right)^{-1} \cdot {}_{PS}^{i}\boldsymbol{BL}_{l}^{T} \cdot {}_{PS}^{i}\boldsymbol{TL}_{l}. \quad (2)$$

Where $[\cdot]^{\boldsymbol{T}}$ and $[\cdot]^{-1}$are as defined in (1), $_{PS}^{i}\boldsymbol{TL}_{l}$ and $_{PS}^{i}\boldsymbol{BL}_{l}$ refer to $n \times 4$ matrices that contain n sample values of the target leads and basis leads respectively, $l \in \{INITwC, INITnoC, SERwC, SERnoC\}$ indicates the dataset from which the training data was taken, n refers to the number of sample values in the average QRS-T complex of each lead and i corresponds to a patient number in the dataset l.

2.4. Derivation of the target leads

The POP based LELT matrix $_{POP}\boldsymbol{A}$ was used to estimate the target leads for each average QRS-T complex in the test datasets $SERnoC$ and $SERwC$. This was performed using (3).

$$_{POP}^{i}\boldsymbol{dTL}^{\boldsymbol{m}} = {}^{i}\boldsymbol{BL}^{\boldsymbol{m}} \cdot {}_{POP}\boldsymbol{A}. \quad (3)$$

Where $_{POP}\boldsymbol{A}$ is as defined in (1), $^{i}\boldsymbol{BL}^{\boldsymbol{m}}$ and $_{POP}^{i}\boldsymbol{dTL}^{\boldsymbol{m}}$ are $n \times 4$ matrices that contain n sample values of the QRS-T complexes from the basis leads and the derived target leads respectively and i identifies a specific subject in the test dataset $m \in \{SERnoC, SERwC\}$.

Each PS LELT matrix was used exclusively for

estimating the target leads of the subject for which the matrix was developed. This was performed for the ordered pairs (l, m) using (4).

$$ {}_{PS}^{i}\boldsymbol{dTL}_{l}^{m} = {}^{i}\boldsymbol{BL}^{m} \cdot {}_{PS}^{i}\boldsymbol{A}_{l} $$

$$ \text{and } (l,m) \in \begin{Bmatrix} (INITnoC, SERnoC), \\ (INITwC, SERwC), \\ (SERnoC, SERnoC), \\ (SERwC, SERwC) \end{Bmatrix}. \quad (4) $$

Where $[\cdot]^{-1}$is as defined in (1), ${}_{PS}^{i}\boldsymbol{A}_{l}$ is as defined in (2), and ${}^{i}\boldsymbol{BL}^{m}$ is as defined in (3), ${}_{PS}^{i}\boldsymbol{dTL}_{l}^{m}$ is a $n \times 4$ matrix that contains n sample values of the QRS-T of the derived target leads, i identifies a specific subject in test datasets $m \in \{SERnoC, SERwC\}$ and training datasets $l \in \{INITnoC, INITwC, SERnoC, SERwC\}$.

2.5. Performance assessment

The estimation performance of the different LELT approaches was quantified using the multistep procedure detailed subsequently.

First, root mean square error (RMSE) values associated with the POP based LELT matrix were determined using (5).

$$ {}_{POP}^{i}\boldsymbol{RMSE}^{m} = \boldsymbol{RMSE}\left({}_{POP}^{i}\boldsymbol{dTL}^{m}, {}^{i}\boldsymbol{TL}^{m}\right). \quad (5) $$

Where ${}_{POP}^{i}\boldsymbol{dTL}^{m}$, m and i are as defined in (3), ${}^{i}\boldsymbol{TL}^{m}$ is a $n \times 4$ matrix that contains n sample values of the QRS-T complexes from the target leads, $RMSE(\cdot)$ is an operator that calculates the RMSE values across the n sample values of each derived target lead separately, ${}_{POP}^{i}\boldsymbol{RMSE}^{m}$ is a 1x4 vector that contains the RMSE values of the four target leads.

Second, RMSE values associated with the different PS LELT matrices were determined using (6).

$$ {}_{PS}^{i}\boldsymbol{RMSE}_{l}^{m} = \boldsymbol{RMSE}\left({}_{PS}^{i}\boldsymbol{dTL}_{l}^{m}, {}^{i}\boldsymbol{TL}^{m}\right). \quad (6) $$

Where ${}_{PS}^{i}\boldsymbol{dTL}_{l}^{m}$, l, m and i are as defined in (4), ${}^{i}\boldsymbol{TL}^{m}$ and $RMSE(\cdot)$ are as define in (5) and ${}_{PS}^{i}\boldsymbol{RMSE}_{l}^{m}$ is a 1x4 vector that contains the RMSE values of the four target leads.

Third, the 1×4 vectors ${}_{POP}^{i}\boldsymbol{RMSE}^{m}$ and ${}_{PS}^{i}\boldsymbol{RMSE}_{l}^{m}$ for all subjects i were used to construct the matrices ${}_{POP}\boldsymbol{RMSE}^{m}$ and ${}_{PS}\boldsymbol{RMSE}_{l}^{m}$.

Fourth, the estimation performance of the different LELT approaches was assessed by calculating the 1×4 mean RMSE vectors ${}_{POP}\overline{\boldsymbol{RMSE}}^{m}$ and ${}_{PS}\overline{\boldsymbol{RMSE}}_{l}^{m}$ using the data in the ${}_{POP}\boldsymbol{RMSE}^{m}$ and ${}_{PS}\boldsymbol{RMSE}_{l}^{m}$ matrices.

Fifth, paired-sample t-tests (significance level a = .05) were conducted to evaluate the statistical significance of the mean differences $\Delta\overline{\boldsymbol{RMSE}}_{INITnoC}^{SERnoC} = {}_{POP}\overline{\boldsymbol{RMSE}}^{SERnoC} - {}_{PS}\overline{\boldsymbol{RMSE}}_{INITnoC}^{SERnoC}$ and $\Delta\overline{\boldsymbol{RMSE}}_{INITwC}^{SERwC} = {}_{POP}\overline{\boldsymbol{RMSE}}^{SERwC} - {}_{PS}\overline{\boldsymbol{RMSE}}_{INITwC}^{SERwC}$. This was performed for each target lead separately.

3. Results

A summary of the findings from our analysis is provided in Table 1 and Table 2.

Table 1. Estimation performance of the POP based LELT matrix and different PS transformation matrices trained using either the $INITnoC$ or $SERnoC$ datasets. The reported estimation performance is quantified as mean RMSE value calculated between the recorded and estimated target leads of the test dataset $SERnoC$.

Target lead	Transformation type		
	${}_{POP}\overline{\boldsymbol{RMSE}}^{SERnoC}$	${}_{PS}\overline{\boldsymbol{RMSE}}_{INITnoC}^{SERnoC}$	${}_{PS}\overline{\boldsymbol{RMSE}}_{SERnoC}^{SERnoC}$
V1	70.8 [56.0; 85.5]	44.9 [34.7; 55.2]*	33.6 [25.1; 42.1]
V3	112.4 [76.7; 148.1]	82.1 [60.3; 104.0]*	44.2 [28.6; 59.9]
V4	115.7 [81.3; 150.1]	72.4 [25.6; 87.2]*	36.0 [29.2; 42.8]
V6	39.6 [27.2; 52.0]	36.0 [25.7; 46.3]	14.0 [10.8; 17.2]

Notes. *mean [95% confidence interval] of the RMSE values associated with a target lead. All values are in μV. Asterisks indicate statistical significance of the differences* ${}_{POP}\overline{\boldsymbol{RMSE}}^{SERnoC} - {}_{PS}\overline{\boldsymbol{RMSE}}_{INITnoC}^{SERnoC}$ *at the ≤ 0.05 level.*

Table 2. Estimation performance of the POP based LELT matrix and different PS transformation matrices trained using either the $INITwC$ or $SERwC$ datasets. The reported estimation performance is quantified as mean RMSE value calculated between the recorded and estimated target leads of the test dataset $SERwC$.

Target lead	Transformation type		
	${}_{POP}\overline{\boldsymbol{RMSE}}^{SERwC}$	${}_{PS}\overline{\boldsymbol{RMSE}}_{INITwC}^{SERwC}$	${}_{PS}\overline{\boldsymbol{RMSE}}_{SERwC}^{SERwC}$
V1	60.5 [48.8; 72.1]	59.3 [48.6; 69.9]	26.6 [20.4; 32.9]
V3	156.0 [120.7; 191.3]	170.8 [129.2; 212.2]	45.9 [32.3;59.5]
V4	80.7 [63.0; 98.4]	69.9 [70.8; 122.9]	26.5 [18.9; 34.2]
V6	51.5 [36.7; 66.2]	76.0 [28.4; 123.6]	12.2 [9.9; 14.4]

Notes. *mean [95% confidence interval] of the RMSE values associated with a target lead. All values are in μV. Asterisks indicate statistical significance of the differences* ${}_{POP}\overline{\boldsymbol{RMSE}}^{SERwC} - {}_{PS}\overline{\boldsymbol{RMSE}}_{INITwC}^{SERwC}$ *at the ≤ 0.05 level.*

4. Discussion

The ${}_{POP}\overline{\boldsymbol{RMSE}}^{SERnoC}$ and ${}_{PS}\overline{\boldsymbol{RMSE}}_{INITnoC}^{SERnoC}$ values in Table 1 quantify the estimation performance of the PS and POP based approach using the same test data. Specifically, the ${}_{PS}\overline{\boldsymbol{RMSE}}_{INITnoC}^{SERnoC}$ values represent the estimation performance of the PS approach in a scenario without ventricular conduction changes between the training and test ECGs. Paired-sample t-tests between the ${}_{POP}\boldsymbol{RMSE}^{SERnoC}$ and ${}_{PS}\boldsymbol{RMSE}_{INITnoC}^{SERnoC}$ values showed that the PS approach has statistically significantly better

estimation performance for most of the target leads, with the exception of target lead V6. This finding is consistent with previous research [13] that has reported higher estimation performance for PS LELTs compared to POP based LELTs.

The values of $_{PS}\overline{RMSE}^{SERnoC}_{INITnoC}$ and $_{PS}\overline{RMSE}^{SERnoC}_{SERnoC}$ presented in Table 1 indicate that the estimation performance of PS LELT matrices is best when they are used to estimate the target leads of their training data. It follows that the estimation performance of the PS approach is high when estimating target leads from excerpts of one ECG recording that exhibits low levels of beat-to-beat variability. Previous research [14] has reported observations that support this conclusion. However, lower levels of estimation performance were observed when the PS LELT matrices were used to estimate the target leads of previously unseen serial ECG data. This finding is consistent with the results of previously published research [14], which attributed the decreased estimation performance to variations in the electrode placement between the training and testing data.

The findings in Table 2 facilitate a comparison of the estimation performance between the PS and POP based approach in a scenario where ventricular conduction changes occur after the training and before the testing of the PS LELT matrices. This comparison can be conducted using the $_{PS}\overline{RMSE}^{SERwC}_{INITwC}$ and $_{POP}\overline{RMSE}^{SERwC}$ values, which quantify the estimation performance of the PS and POP based approaches, based on the same test data. Paired-sample t-tests between $_{PS}RMSE^{SERwC}_{INITwC}$ and $_{POP}RMSE^{SERwC}$ values show no statistically significant difference in the estimation performance between the PS and the POP based approach. This was true for all target leads.

5. Conclusion

The most pronounced advantage of the PS over the POP based approach can be expected when the training and the testing of PS LELTs is conducted using excerpts of ECG recordings that exhibit low levels of beat-to-beat variability. However, the magnitude of this advantage will reduce when PS LELTs are tested on serial ECGs. This reduction was observed even in the absence of changes in ventricular conduction between the training and testing ECGs. A further reduction in the estimation performance of PS LELTs occurs when ventricular conduction changes develop after training and before performance testing on serial ECGs. In this scenario, no advantage of the PS approach over the POP based approach was observed.

Estimation performance values of PS LELTs that are based on excerpts from one ECG recording with low beat-to-beat variability are very optimistic. Performance values based on such an assessment are only meaningful if it is intended to utilize the assessed LELTs for one recording and in situations with low beat-to-beat variability.

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