

Influence of the Training Set Composition on the Estimation Performance of Linear ECG-Lead Transformations

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Abstract

Linear ECG-lead transformations (LELTs) are used to estimate unrecorded target leads by applying a number of recorded basis leads to a LELT matrix. Such LELT matrices are commonly developed using training datasets that are composed of ECGs that belong to different diagnostic classes (DCs).

The aim of our research was to assess the influence of the training set composition on the estimation performance of LELTs that estimate target leads V1, V3, V4 and V6 from basis leads I, II, V2 and V5 of the 12-lead ECG. Our assessment was performed using ECGs from the three DCs left ventricular hypertrophy, right bundle branch block and normal (ECGs without abnormalities).

Training sets with different DC compositions were used for the development of LELT matrices. These matrices were used to estimate the target leads of different test sets. The estimation performance of the developed matrices was quantified using root mean square error values calculated between derived and recorded target leads.

Our findings indicate that unbalanced training sets can lead to LELTs that show large estimation performance variability across different DCs. Balanced training sets were found to produce LELTs that performed well across multiple DCs. We recommend balanced training sets for the development of LELTs.

1. Introduction

Linear electrocardiographic (ECG) lead transformations (LELTs) are used to estimate or derive unrecorded target leads by applying a number of recorded basis leads to a LELT matrix [1, 2]. LELTs are a well-established concept in computerized electrocardiography. Two main application areas of LELTs have been established.

One of these established application areas is the estimation of leads that are not commonly recorded in

clinical practice. The estimation of these leads is typically performed using ECGs that are recorded in a standard format. One example for this application area is the estimation of the Frank vectorcardiogram (VCG) [3] from the Mason-Likar [1] or the standard 12-lead ECG [4]. This estimation is performed as the Frank VCG is thought to offer prognostic and diagnostic information that is in addition to the information contained in the 12-lead ECG. A further example of this application area is the estimation of device specific leads. This approach allows for the utilization of estimated device specific leads, that are obtained from existing standard 12-lead ECG databases, for the performance assessment of ECG devices that make use of non-standard ECG leads [5].

The other established application area of LELTs are reduced lead systems. These systems aim to estimate unrecorded leads of the 12-lead ECG [6] or the Frank VCG [2] from a reduced number of monitoring compatible electrodes. Such LELTs are used in continuous ECG monitoring applications where the information provided by the estimated lead sets is of interest, but the direct recording of the estimated lead set would be challenging due to electrode locations that are not suitable for continuous ECG monitoring.

LELT matrices are commonly developed using training sets and multivariate linear regression analysis [3, 6]. Training sets typically contain ECG data from different subjects and contain ECGs that belong to different diagnostic classes. The composition of the diagnostic classes in the training sets used for the development of LELTs is thought to have an influence on the estimation performance of the developed LELT matrices. However, a systematic assessment of the extent of this influence has, to the best of our knowledge, not been reported in literature.

The aim of our research was to assess what influence the composition of the diagnostic classes in a training set has on the estimation performance of LELTs. This assessment was conducted on a set of 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. Study population

Our study population was composed of 229 subjects with no abnormalities in their ECGs (normal), 232 subjects with left ventricular hypertrophy (LVH) and 250 subjects with right bundle branch block (RBBB). Random sampling without replacement was used to generate 200 different instances for each of the train and test set compositions outlined in Table 1. This was performed using ECG data of the diagnostic classes normal, LVH and RBBB obtained from the subjects in the study population.

Table 1. Train and test set compositions.

name	type ^a	composition		
		#norm ^b	#LVH ^c	#RBBB ^d
TRnorm	train	171	0	0
TRlvh	train	0	171	0
TRrbbb	train	0	0	171
TRmix	train	57	57	57
TEnorm	test	55	0	0
TElvh	test	0	55	0
TErbbb	test	0	0	55

Notes. ^atrain indicates a dataset composition that was used for the generation of LET matrices and test indicates a dataset composition that was used for the performance assessment of LET matrices; ^bnumber of ECGs of normal subjects in the composition; ^cnumber of ECGs of LVH subjects in the composition; ^dnumber of ECGs of RBBB subjects in the composition.

2.2. ECG data

Standard 12-lead ECG data of different sources was used in this research. The standard 12-lead ECG data of 229 normal and 232 LVH subjects was extracted from body surface potential maps (BSPMs). Each BSPM contained electro-cardiographic 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 [7]. A Laplacian 3D interpolation procedure [8] was applied to the 117 thoracic BSPM leads. This was performed to obtain body surface potentials at the locations of the 352 Dalhousie torso [9] 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 [10]. 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.

The standard 12-lead ECG data of 250 subjects with RBBB was assembled using the data in [11] and [12]. First, the annotations provided in [11] were used to identify 10 second 12-lead ECGs from different subjects with complete and incomplete RBBB. Second, average beats that were created using the Glasgow ECG program were obtained from [12]. Third, QRS-T complexes of the average beats were manually annotated and subsequently isolated.

2.3. Target and basis lead configuration

As stated earlier one established application area of LETs are reduced lead systems. A reduced lead system that has been extensively studied [6] and has also been adopted into clinical practice [13] estimates the target leads V1, V3, V4 and V6 by applying a LET matrix to the basis leads I, II, V2 and V5 of the Mason-Likar [1] 12-lead ECG. We assess the influence of the training set composition on the estimation performance of LET matrices that estimate the target leads V1, V3, V4 and V6 using the basis leads I, II, V2 and V5 of the standard (distal limb leads) 12-lead ECG.

2.4. Development of the LET matrices

The different training set instances were used to generate 200 LET matrices for each training set composition. Individual LET matrices were developed using the multivariate linear regression approach in (1).

$${}^i_m\mathbf{A} = ({}^i_m\mathbf{BL}^T \cdot {}^i_m\mathbf{BL})^{-1} \cdot {}^i_m\mathbf{BL}^T \cdot {}^i_m\mathbf{TL}. \quad (1)$$

Where $[\cdot]^T$ and $[\cdot]^{-1}$ denote the transpose and the inverse of a matrix respectively, ${}^i_m\mathbf{A}$ refers to a 4×4 matrix of transformation coefficients that allows for the transformation of the basis leads into the target leads, $m \in \{TRnorm, TRlvh, TRrbbb, TRmix\}$ denote the composition of the training set, n refers to the number of sample values of the 171 QRS-T complexes in each lead of the training set, $i \in \{1, \dots, 200\}$ denotes the instance of the training set that was used for the development of ${}^i_m\mathbf{A}$, ${}^i_m\mathbf{TL}$ refers to a $n \times 4$ matrix that contains n sample values of the target leads and ${}^i_m\mathbf{BL}$ refers to a $n \times 4$ matrix that contains n sample values of the basis leads.

2.5. Derivation of the target leads

Each ${}^i_m\mathbf{A}$ matrix was used to derive the target leads of three test sets. These test sets were assembled in accordance to one of the test set compositions $k \in \{TEnorm, TElvh, TErbbb\}$ detailed in Table 1. The target lead derivation was performed using the approach in (2).

$${}^i_m\mathbf{dTL}_k = {}^i_k\mathbf{BL} \cdot {}^i_m\mathbf{A}. \quad (2)$$

Where ${}^i_m\mathbf{A}$, m and i are as defined in (1), ${}^i_k\mathbf{BL}$ is a $n \times 4$ matrix that contains the n sample values of the QRS-T

complexes from the basis leads of one subject in the test dataset and $m^i dTL_k$ is a $n \times 4$ matrix that contains the n sample values of the QRS-T complexes of the derived target leads.

2.6. Performance assessment

The influence of the training set composition on the estimation performance of the LETs under investigation was assessed as detailed subsequently.

First, root mean square error (RMSE) values were calculated between the QRS-T complexes of the recorded and the derived target leads.

Second, the population RMSE and the population subject to subject variability (SSV) were determined for each $m^i A$ using test data of the corresponding test set instance i . The population RMSE and population SSV were defined as the mean and the standard deviation of the RMSE values respectively. Values for the population RMSE and for the population SSV were determined over the 55 RMSE values per target lead and test set of each instance i . The outcome of this assessment were multiple $m^i PRMSE_k$ and $m^i PSSV_k$ matrices with $m \in \{TRnorm, TRlvh, TRrbbb, TRmix\}$ and $k \in \{TEnorm, TElvh, TErbbb\}$. Where $m^i PRMSE_k$ and $m^i PSSV_k$ are 200×4 matrices that contain the values of the population RMSE and the population SSV of the four target leads for each of the 200 instances i respectively.

Third, the estimation performance associated with a training set composition m was assessed for the different test set compositions k . The estimation performance was quantified as mean population RMSE ($m^i PRMSE_k$) and mean population SSV ($m^i PSSV_k$) values. Where $m^i PRMSE_k$ and $m^i PSSV_k$ are 1×4 vectors that were computed by calculating the mean over the 200 rows of the corresponding $m^i PRMSE_k$ and $m^i PSSV_k$ matrices.

Forth, the mean (95% confidence interval) of the differences $m^i PRMSE_k - mix^i PRMSE_k$ and $m^i PSSV_k - mix^i PSSV_k$ was calculated for all combinations $(m, k) = \{(TRnorm, TEnorm), (TRlvh, TElvh), (TRrbbb, TErbbb)\}$ in which m and k belong to the same diagnostic class. This was performed across the 200 differences associated with each target lead.

Fifth, the statistical significance of the differences in the mean population values $m^i PRMSE_k - mix^i PRMSE_k$ and $m^i PSSV_k - mix^i PSSV_k$ was assessed for all $m \in \{TRnorm, TRlvh, TRrbbb\}$ and $k \in \{TEnorm, TElvh, TErbbb\}$ using a two-tailed paired t-test (alpha level of significance .05).

3. Results

A summary of the findings from our analysis is provided in Table 2 and Table 3 for target leads V1 and V3 respectively. The findings for target leads V4 and V6 were similar to what can be observed in Table 2 and Table 3 and are omitted for brevity.

Table 2. Estimation performance [mean population RMSE; mean population SSV] associated with target lead V1 for the different train and test set compositions under investigation.

Test	Train				difference ^a
	TRnorm	TRlvh	TRrbbb	TRmix	
TEnorm	[102.5*;	[115.3*;	[132.1*;	[109.1;	6.5 [6.1; 7.0]
	45.4*]	51.7*]	56.7*]	46.0]	0.7 [0.3; 1.0]
TElvh	[111.1*;	[103.1*;	[136.1*;	[106.9;	3.8 [3.3; 4.2]
	91.9*]	81.1*]	85.9*]	82.5]	1.4 [0.8; 2.1]
TErbbb	[120.4*;	[117.2*;	[103.6*;	[109.8;	6.2 [5.6; 6.8]
	74.6*]	72.5*]	56.6*]	67.9]	11.3 [10.8; 11.8]

^amean (95% confidence interval) of the differences $m^i PRMSE_k - mix^i PRMSE_k$ and $m^i PSSV_k - mix^i PSSV_k$ for $(m, k) = \{(TRnorm, TEnorm), (TRlvh, TElvh), (TRrbbb, TErbbb)\}$. Notes. All values are in μV . Asterisks indicate statistical significance of the differences $m^i PRMSE_k - mix^i PRMSE_k$ and $m^i PSSV_k - mix^i PSSV_k$ for $m \in \{TRnorm, TRlvh, TRrbbb\}$ and $k \in \{TEnorm, TElvh, TErbbb\}$ at the ≤ 0.05 level.

Table 3. Estimation performance [mean population RMSE; mean population SSV] associated with target lead V3 for the different train and test set compositions under investigation.

Test	Train				difference ^a
	TRnorm	TRlvh	TRrbbb	TRmix	
TEnorm	[104.4*;	[171.1*;	[146.4*;	[128.0;	23.6 [22.2; 25.0]
	61.8*]	85.1*]	78.3*]	69.5]	7.7 [6.7; 8.8]
TElvh	[183.0*;	[144.3*;	[150.6*;	[153.8;	9.5 [8.5; 10.6]
	174.1*]	108.6*]	107.2*]	121.3]	12.6 [10.7; 14.5]
TErbbb	[125.7*;	[120.6*;	[117.7*;	[118.1;	0.4 [0.1; 0.7]
	82.6*]	72.2*]	73.6*]	74.5]	0.9 [0.5; 1.3]

^amean (95% confidence interval) of the differences $m^i PRMSE_k - mix^i PRMSE_k$ and $m^i PSSV_k - mix^i PSSV_k$ for $(m, k) = \{(TRnorm, TEnorm), (TRlvh, TElvh), (TRrbbb, TErbbb)\}$. Notes. All values are in μV . Asterisks indicate statistical significance of the differences $m^i PRMSE_k - mix^i PRMSE_k$ and $m^i PSSV_k - mix^i PSSV_k$ for $m \in \{TRnorm, TRlvh, TRrbbb\}$ and $k \in \{TEnorm, TElvh, TErbbb\}$ at the ≤ 0.05 level.

4. Discussion

The findings in Table 2 and Table 3 show lowest $PRMSE$ values (highest estimation performance) when LET matrices are developed and tested on ECGs belonging to the same diagnostic class. This suggests that the estimation performance of the LETs under investigation can be optimized for ECGs that belong to one of the assessed diagnostic classes.

However, from the findings in Table 2 and Table 3 it can be seen that the estimation performance ($PRMSE$ and $PSSV$) of LET matrices that are trained on only one of the assessed diagnostic classes does decrease notably when such a matrix is applied to ECGs that belong to a different

diagnostic class. Considering that, in a clinical setting, ECGs belonging to different diagnostic classes will be applied to LELET matrices it is evident that the practical utility of selectively trained LELET matrices is limited.

Interestingly, the findings in Table 2 and Table 3 show that the utilization of the balanced training set composition $m = TR_{mix}$ does lead to LELET matrices that have good levels of estimation performance across the different assessed diagnostic classes. More precisely, the estimation performance of such LELET matrices was found to be close to the performance achieved by LELET matrices that were designed for and used on a specific diagnostic class.

The literature typically reports the estimation performance of LELET matrices over test sets containing ECGs that belong to multiple diagnostic classes. However, the findings in Table 3 show differences in the estimation performance across different diagnostic classes. Such as for example across the $_{mix}PRMSE_k$ values for $k \in \{T_{norm}, T_{Elvh}, T_{Erbbb}\}$. The composition of the utilized test set does therefore influence the observed estimation performance. A consequence of this is that a meaningful comparison of RMSE-based estimation performance values reported in the literature is only possible if they were obtained from similarly composed test sets.

This research has assessed the influence of the training set composition for the estimation performance of LELET matrices based on a particular configuration of target and basis leads. However, we speculate that similar findings can be obtained for LELET matrices based on other lead configurations.

A limitation of this research is that it has only assessed the influence of the training set composition on the waveform reconstruction error (RMSE between derived and recorded target leads). The extent to which the training set composition does influence the diagnostic interpretation of reconstructed ECGs has not been assessed.

5. Conclusion

The composition of the training set was found to have an influence on the estimation performance of the LELETs under investigation. Our findings indicate that unbalanced training sets can lead to biased LELET matrices. The estimation performance of such biased LELET matrices was found to vary notably across different diagnostic classes. This variability in the estimation performance may not be tolerable in clinical settings where LELET matrices will be applied to ECGs that belong to different diagnostic classes. However, balanced training sets were found to produce LELET matrices that performed well over different diagnostic classes. We recommend the utilization of balanced training sets, that reflect the diagnostic classes of the target population, for the development of LELET matrices.

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