María Hernández Mesa*, Nicolas Pilia, Olaf Dössel, and Axel Loewe

Influence of ECG Lead Reduction Techniques for Extracellular Potassium and Calcium Concentration Estimation

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Abstract: Chronic kidney disease (CKD) affects 13% of the worldwide population and end stage patients often receive haemodialysis treatment to control the electrolyte concentrations. The cardiovascular death rate increases by 10% - 30% in dialysis patients than in general population. To analyse possible links between electrolyte concentration variation and cardiovascular diseases, a continuous non-invasive monitoring tool enabling the estimation of potassium and calcium concentration from features of the ECG is desired. Although the ECG was shown capable of being used for this purpose, the method still needs improvement. In this study, we examine the influence of lead reduction techniques on the estimation results of serum calcium and potassium concentrations. We used simulated 12 lead ECG signals obtained using an adapted Himeno et al. model. Aiming at a precise estimation of the electrolyte concentrations, we compared the estimation based on standard ECG leads with the estimation using linearly transformed fusion signals. The transformed signals were extracted from two lead reduction techniques: principle component analysis (PCA) and maximum amplitude transformation (MaxAmp). Five features describing the electrolyte changes were calculated from the signals. To reconstruct the ionic concentrations, we applied a first and a third order polynomial regression connecting the calculated features and concentration values. Furthermore, we added 30 dB white Gaussian noise to the ECGs to imitate clinically measured signals. For the noise-free case, the smallest estimation error was achieved with a specific single lead from the standard 12 lead ECG. For example, for a first order polynomial regression, the error was 0.0003±0.0767 mmol/l (mean±standard deviation) for potassium and -0.0036±0.1710 mmol/l for calcium (Wilson lead V1). For the noisy case, the PCA signal showed the best estimation performance with an error of -0.003±0.2005 mmol/l for potassium and -0.0002±0.2040 mmol/l for calcium (both first order fit). Our results show that PCA as ECG lead reduction technique is more robust against noise than MaxAmp and standard ECG leads for ionic concentration reconstruction.

Keywords: ECG, PCA, lead reduction techniques, cardiac signals, ionic concentrations

1 Introduction

Chronic kidney disease (CKD) patients at end stages often undergo haemodialysis treatments to counterbalance the electrolyte disbalance. Unexpectedly, the principal mortality cause for CKD patients is sudden cardiac death. The risk of cardiac mortality is 10 to 30 times higher in CKD patients than in non-CKD patients [1]. Recent studies have shown the relationship between the extracellular potassium ($[K^+]_o$), and calcium ($[Ca^{2+}]_o$) concentrations and the pathophysiology of sudden cardiac death [2]. Due to this connection, ECG has been proposed as a non-invasive method to determine the blood serum electrolyte concentrations. A reduction of the information of a 12 lead ECG to a set of most discriminating input data is desired. In 2011, Corsi et al. [3] used a PCA transform of clinical ECG signals for this purpose. Other works in this field [4] used a lead transformation in the direction of the highest amplitude (MaxAmp) for lead reduction. A comparison between the mentioned lead reduction techniques (PCA and MaxAmp) is still lacking. Furthermore, no studies comparing lead transforms and standard leads for the regression are known to the authors of this work. Additionally, different regression methods, such as neuronal networks or polynomial fit can be applied for the same purpose. The ECG as an electrolyte and a cardiac event predictor is a promising tool, which has shown results with a standard deviation smaller than 0.2 mmol/l for $[Ca^{2+}]_o$ and 0.4 mmol/l for $[K^+]_o$. However, many parameters and techniques still have to be optimized to obtain a robust and precise tool for electrolyte estimation. In this study, we compare the concentration estimation results based on simulated signals from ECG lead reduction techniques (PCA and MaxAmp) and the results from single lead reconstruction from the 12 lead ECG. We performed an evaluation for both noisy and noise-free cases. Moreover, we applied polynomial regression with a first and a third order polynomial fit to investigate on the influence of the lead reduction techniques on those two regres-

***Corresponding author: María Hernández Mesa,** Institute of Biomedical Engineering, Karlsruhe Institute of Technology (KIT), Kaiserstr. 12, 76131 Karlsruhe, Germany, E-mail: publications@ibt.kit.edu
Nicolas Pilia, Olaf Dössel, Axel Loewe, Institute of Biomedical Engineering, Karlsruhe Institute of Technology (KIT), Karlsruhe, Germany

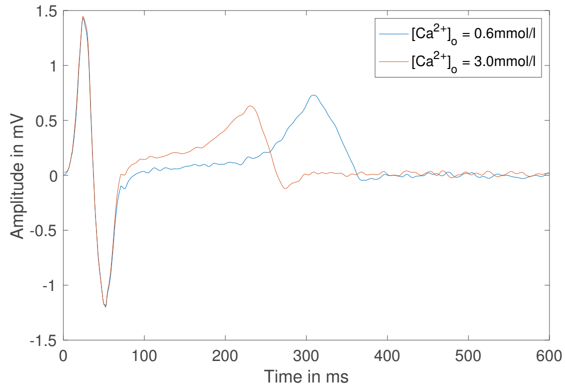

Fig. 1: Two exemplary simulated ventricular ECG signals at different $[Ca^{2+}]_o$ levels corrupted by 30dB white Gaussian noise (lead Einthoven 1).

sion methods. This allowed us to appraise which combination is adequate for our objective of estimating $[Ca^{2+}]_o$ and $[K^+]_o$.

2 Methods

2.1 Simulations

80 computer simulations of the cardiac electrophysiology at ventricular level were performed. The heterogeneous formulation from the Himeno et al. [5] model proposed by Loewe et al. [6] was used. In the original formulation $[K^+]_o$ was set to 4.5 mmol/l and $[Ca^{2+}]_o$ to 1.8 mmol/l. In this study, we varied the ionic concentrations in equally distributed steps as in a former study [4]. Further settings were applied as described there. Since a ventricular cell model was used, no P wave was contained in the extracted ECG signals. For a realistic simulation of the pathophysiological cases, we added noise to the simulated signals. We added white Gaussian noise to the signals achieving an SNR of 30 dB. As in clinically measured ECG signals, we low-pass filtered the noise signals with a cut-off frequency of 80 Hz using a butterworth 6th order phase free filter. The low-pass filtered noise signals were added to each setup of the ECG simulated signals. The generation of noise signals was repeated 30 times per setup to augment the dataset as described in [7]. This allowed us to augment the data set. The addition of noise to the ECG signals and the influence of $[Ca^{2+}]_o$ on the ECG can be observed in Figure 1.

2.2 Lead reduction

For the ionic concentration estimation, features from ECG signals were extracted as described in [7]. The following features were used for further steps: center of the T wave, amplitude of the T wave, upslope of the T wave, ratio of energy of the second half of the T wave to the energy of the whole T wave, and R amplitude. Feature estimation was applied to signals from three different combinations. The first combination was a standard 12 lead ECG. Thus, the features from all 12 signals were calculated. The second combination used MaxAmp as ECG lead reduction technique. MaxAmp lead reduction was applied in the direction of the QRS complex and in the direction of the T wave; i.e., 2 signals were calculated with this reduction method. Features related to changes in the QRS complex were extracted from the MaxAmp signal that maximized R peak amplitude and features regarding changes of the shape and amplitude of the T wave were extracted from the MaxAmp signal that maximized T wave amplitude. The third combination used the PCA as lead reduction technique. PCA was applied to the 8 linearly independent ECG leads. The QRS complex generally has a higher amplitude than the T wave, thus the first component of the PCA (PCA 1^{st}) is higher influenced by this part of the signal. Therefore, we also calculated the second component of the PCA (PCA 2^{nd}) and additionally the PCA of the signal part containing the T wave (PCA T). Therefore, the impact of both parts of the signal could be observed, especially considering that changes of $[Ca^{2+}]_o$ and $[K^+]_o$ have a dominant influence on the T wave [8]. Summarizing, features were calculated for the 17 signals extracted from all combinations (12 leads, 2 signals from MaxAmp and 3 signals from the PCA technique).

2.3 Regression

Polynomial regression was chosen for reconstructing ionic concentrations of $[K^+]_o$ and $[Ca^{2+}]_o$ from the feature values. For the validation of the methods, 20-fold cross validation was used. The grouping of the setups was the same for all input setups and for all regression techniques. The estimation error was determined and minimized for each partition data using a Tikhonov regularization.

3 Results

Figure 2 and 3 show the results of applying different lead reductions techniques to a standard 12 lead ECG and MaxAmp respectively. For both analyzed ionic concentrations ($[K^+]_o$ and $[Ca^{2+}]_o$), estimation performance was evaluated by analyzing the mean error and the standard deviation of the errors. Results are summarized in Tables 1 and 2. Table 1 shows the estimation errors using a polynomial fit of first order as re-

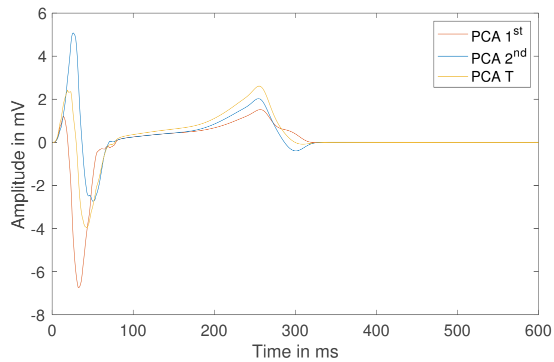

Fig. 2: Signals resulting from an information reduction of a standard ECG using PCA.

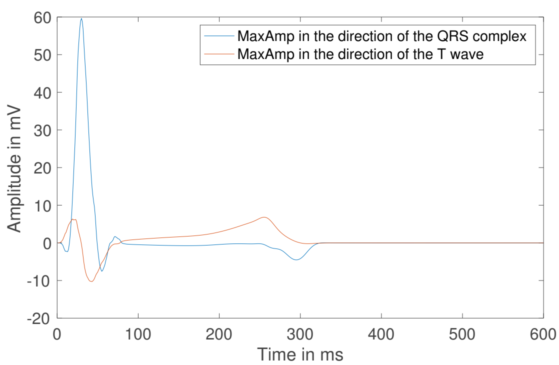

Fig. 3: Signals resulting from an information reduction of a standard ECG using a MaxAmp transformation.

gression method, Table 2 using a third order polynomial fit. The upper part of the table shows the results for the noise-free case and the lower part for the noisy case. For the regression using a standard 12 lead ECG without reduction techniques the estimation error was calculated for each lead. The results depict the lead with the smallest estimation error (best lead).

For noise-free signals and a first order polynomial regression, Wilson lead V1 showed the smallest standard deviation and MaxAmp the highest standard deviation of the estimation . When applying noise, the second component of the PCA yielded the smallest standard deviation of errors. There are discrepancies between the results using a first order and a third order polynomial regression model. For a third order polynomial regression, Wilson lead V1 and PCA T showed the smallest standard deviation of errors for $[K^+]_o$ and $[Ca^{2+}]_o$ respectively for the noise-free case; PCA T and PCA 2nd for the noisy case. The highest standard deviation for the $[K^+]_o$ estimation error was obtained when using a PCA 1st as lead reduction technique for both the noisy and noise-free case for a third order polynomial fit. For $[Ca^{2+}]_o$, the highest standard deviation of errors ocurred when using MaxAmp for noise-free signals and

Tab. 1: Influence of different lead reduction techniques on a first order regression. Estimation errors represent mean error ± standard deviation. The smallest and highest standard deviation of errors per regression method are highlighted in green and red, respectively.

noise-free	$[K^+]_o$ in mmol/l	$[Ca^{2+}]_o$ in mmol/l
PCA 1st	-0.0072±0.2778	0.0034±0.2148
PCA 2nd	-0.0054±0.1857	0.0038±0.2055
PCA T	-0.0049±0.2152	0.0021±0.1938
MaxAmp	-0.0004±0.3159	-0.0057±0.5379
V1/V1 (best lead)	0.0003±0.0767	-0.0036±0.1710
noisy	**$[K^+]_o$ in mmol/l**	**$[Ca^{2+}]_o$ in mmol/l**
PCA 1st	-0.0001±0.9830	0.0001±0.7394
PCA 2nd	-0.003±0.2005	-0.0002±0.2040
PCA T	-0.0036±0.2376	-0.001±0.2128
MaxAmp	-0.0019±0.3412	0.0099±0.6556
V2/V2 (best lead)	-0.0003±0.8321	-0.0011±0.7482

Wilson lead V2 for noisy signals. Additionally we observed that the standard deviation of error for a 12 lead standard ECG increased more than for MaxAmp and PCA.

4 Discussion

Similar to the studies by Corsi et al. [2] and Pilia et al. [3] the ionic concentration estimation errors showed an acceptable range. The results underline that the estimation errors highly depend on the regression method, the prevalence of noise and the lead or lead reduction technique used. In both regression methods, the estimation error of ECG lead regression with single leads of the ECG in noise-free signals showed smaller standard deviation of the errors. Due to the results presented in the previous section, we consider that for noise-free signals using a standard 12 lead ECG achieves better results than using lead reduction techniques. We believe it is worth to mention that except for $[K^+]_o$ estimation with a first order polynomial fit, MaxAmp showed the highest standard deviation of errors for all combinations. When considering noisy signals, the lowest standard deviation of error was achieved for PCA 2nd or PCA T. The biggest standard deviation of errors were obtained by either the first component of the PCA or the single ECG lead estimation in both regression models. Lead reduction techniques are apparently more robust against noise than a standard 12 lead ECG as visible in Table 1 and 2. Thus, when working with noisy signals, a lead reduction technique should be used. In this study, applying PCA 2nd or a PCA T showed the best results. As electrolyte variation has a higher impact on the T wave than on the QRS complex for the evaluated features, we have shown with this study how im-

Tab. 2: Influence of different lead reduction techniques on a third order regression. Estimation errors represent mean error ± standard deviation. The smallest and highest standard deviation of errors per regression method are highlighted in green and red, respectively.

noise-free	$[K^+]_o$ in mmol/l	$[Ca^{2+}]_o$ in mmol/l
PCA 1st	-0.0416±0.3591	0.0158±0.1465
PCA 2nd	-0.0288±0.2733	0.0126±0.1251
PCA T	-0.0112±0.1076	0.0025±0.0714
MaxAmp	-0.0072±0.1579	0.0256±0.4659
V1/II (best lead)	0.0026±0.0663	0.0012±0.0747
noisy	**$[K^+]_o$ in mmol/l**	**$[Ca^{2+}]_o$ in mmol/l**
PCA 1st	0.0007±0.9863	0.0008±0.7445
PCA 2nd	-0.01±0.1736	0.0011±0.0810
PCA T	-0.0037±0.1579	-0.0005±0.1094
MaxAmp	0.0016±0.2734	-0.0084±0.6084
V2/V2 (best lead)	0.001±0.8339	-0.0012±0.7518

portant a lead reduction in the correct direction is. This can be observed by comparing the results of PCA 1st with the results of PCA 2nd and PCA T. We consider relevant to mention that MaxAmp showed higher standard deviation of errors than the errors obtained from using PCA 2nd and PCA T. Additionally, we observed the smallest standard deviation of errors using a third order polynomial fit instead of a first order polynomial fit. Therefore, third order polynomial fit is a better suited regression method when aiming at a serum blood estimation of $[K^+]_o$ and $[Ca^{2+}]_o$ using the ECG because non-linear behaviour between features and ionic concentrations can be better captured. The following limitations should be taken into account regarding this study. On the one hand, the evaluation of the influence of ECG lead reduction techniques has been carried out for simulated signals. Although we added noise to the signals to reproduce a more realistic scenario, the results using clinical data may differ from the results presented here. We observed that the estimation errors depend on the regression method used. In this study, we have analyzed a first order and a third order polynomial fit. However, when utilizing other regression models like for example neuronal networks, the results may vary. We evaluated the results of lead reduction as we suspect that too many features can decrease the accuracy of the estimation. However, we did not prove if the full information of the 12-lead ECG would deliver better results.

5 Conclusions

In this work, we used simulated signals with the adapted Himeno et al. model to study the influence of ECG lead reduction techniques on ionic concentration estimation. Therefore, we used 2 different regression methods and were able to show, that the third order polynomial regression yielded smaller standard deviation of estimation errors than a first order polynomial fit. We showed that for the noise-free case, using single leads of the ECG reached generally better results than using signals obtained by lead reduction techniques like PCA or MaxAmp. However, when adding noise to the signals, a lead reduction using principal component analysis showed generally the best results. This supports the promising idea of using ECG as a non invasive method for $[K^+]_o$ and $[Ca^{2+}]_o$ estimation and the subsequent prediction of cardiac events in CKD patients.

Author Statement
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