Acta Cardiol Sin 2021;37:47–57
Original Article
doi: 10.6515/ACS.202101_37(1).20200712A

EP & Arrhythmia

The Reconstruction of a 12-Lead Electrocardiogram from a Reduced Lead Set Using a Focus Time-Delay Neural Network

Gerard H. Smith, Dawie J. Van den Heever and Wayne Swart

Background: The 12-lead electrocardiogram (ECG) is the gold-standard ECG method used by cardiologists. However, accurate electrode placement is difficult and time consuming, and can lead to incorrect interpretation.
Objectives: The objective of this study was to accurately reconstruct a full 12-lead ECG from a reduced lead set.
Methods: Five-electrode placement was used to generate leads I, II, III, aVL, aVR, aVF and V2. These seven leads served as inputs to the focus time-delay neural network (FTDNN) which derived the remaining five precordial leads (V1, V3-V6). An online archived medical database containing 549 cases of ECG recordings was used to train, validate and test the FTDNN.
Results: After removing outliers, the reconstructed leads exhibited correlation values of between 0.8609 and 0.9678 as well as low root mean square error values of between 123 μV and 245 μV across all cases, for both healthy controls and cardiovascular disease subgroups except the bundle branch block disease subgroup. The results of the FTDNN method compared favourably to those of prior lead reconstruction methods.
Conclusions: A standard 12-lead ECG was successfully reconstructed with high quantitative correlations from a reduced lead set using only five electrodes, of which four were placed on the limbs. Less reliance on precordial leads will aid in the reduction of electrode placement errors, ultimately improving ECG lead accuracy and reduce the number of cases that are incorrectly diagnosed.

Key Words: ECG • Electrocardiography • Focus time-delay neural network • Neural networks • Reconstruct 12-lead ECG • Reduced lead set ECG

INTRODUCTION

The electrocardiogram (ECG) is one of the most commonly used medical devices in cardiology and has been trusted by healthcare professionals since its introduction. It is used as a non-invasive method to record and monitor the heart's electrical bio-signals during the cardiac cycle, and assist physicians in diagnosing cardiovascular disease (CVD). In the years following the introduction of the ECG, vectorcardiography systems with various electrode placements have been developed with the most popular being Burger and Van Milaan,[1] McFee and Parungao,[2] Schmitt and Simonson[3] and Frank.[4] However, 12-lead ECG remains the gold-standard method used by cardiologists. The various leads are categorised as bipolar limb leads (I, II, III), augmented unipolar limb leads (aVR, aVL, aVF) and unipolar precordial leads (V1-V6). Due to the manner in which leads I-III, aVR, aVL and aVF are derived, as well as the close positional proximity of the precordial leads, many of the ECG leads contain information from the same region of the heart.[5] This presents the possibility of exploiting repeated local infor-

Received: June 14, 2019 Accepted: July 12, 2020
Biomedical Engineering Research Group, Department of Mechanical and Mechatronic Engineering, Stellenbosch University, South Africa. Corresponding author: Dr. Dawie J. van den Heever, Room 3033, Department of Mechanical and Mechatronic Engineering, Corner of Banghoek and Joubert Street, Stellenbosch, 7600, South Africa. Tel: +27(0) 21 808 4856; E-mail: dawie@sun.ac.za

mation from a reduced lead set and using it to interpolate missing leads.

Previous studies relating to lead reconstruction have focused on either ECG or vectorcardiogram (VCG) leads. Dimensionality reduction techniques such as principle component analysis, also known as abstract factor analysis, have been used in the past to successfully identify redundant leads,[5-7] and various studies have attempted to reconstruct absent leads from different configurations of reduced lead sets, with varying success.[6,8-12]

Prior studies[13-15] have used linear transforms to create a matrix of basis leads consisting of coefficients, known as a "Dower universal transform" that can be used to reconstruct any absent leads. This method was an ideal "one-size-fits-all" solution with questionable accuracy due to the coefficients' dependence on various biological and environmental factors within the population that exhibit significant variability.[16,17] Schreck et al.[6,18] used the simplex non-linear optimisation method to construct a universal transformation matrix which could be used to reconstruct missing leads. The base leads used in reconstructing the remaining 12-lead ECG, by virtue of the universal transform matrix, initially included leads I, aVF and V2,[18] with later work focusing on I, II and V2.[6]

Universal transforms were preceded by "population-specific transforms" which categorised patients under headings based on their gender, age and disease classification. This strategy resulted in a transform that was more customised to the patient in an attempt to increase accuracy. Independent component analysis was used to generate a third transform, known as "patient-specific transform", which reconstructs missing leads from a reduced lead set, tailored to a specific patient.[8,9] Initially, all 12 leads are required to calibrate the transform coefficients, after which the leads are removed and subsequently reconstructed at a later stage.

Nelwan et al.[10] used a reduced lead system known as the "EASI" ECG, in which five electrodes were placed at simple anatomical locations found using landmarks on the thorax to create a derived 12-lead ECG. These landmark positions were based on the Frank lead system in which the leads are reconstructed using the empirically obtained transform coefficients. This method was developed from the heart dipole hypothesis that underlines vectorcardiography. The EASI lead produces three non-orthogonal leads, of which all other leads are reconstructed using algebraic calculations. This is achieved by using linear combinations of the three non-orthogonal leads and the transformation coefficients.

Drew et al.[9] used an unconventional five-lead wire system. The optimal electrode positions were determined by optimising the root mean square error (RMSE) between the true leads and the reconstructed leads. The process was repeated in 20 patients using 16 potential locations, and resulted in the use of Mason-Likar (M-L) electrode placement positions for electrodes RA, LA and LL, in which these limb electrodes are relocated onto the thorax. In this system, the LL electrode is placed in the 6th intercostal space at the left mid-clavicular line, which is located just below the standard V4 lead position, and a chest electrode is placed in the 4th intercostal space in the middle of the left mid-clavicular line and the left sternal border, close to the standard V3 lead position.

In the current study, we used an artificial neural network (ANN), which was initially introduced in 1943. ANNs have increased in popularity in recent years, which can be attributed to the steep increase in computational performance and processing power that has become readily available and easily accessible.[19] An ANN is an artificial intelligence and machine learning technique that was conceptualised from knowledge of how human biological neural networks function, and ANNs are believed to be a promising solution to enable machines to solve intricate problems. This technique is capable of identifying pertinent features from inputted data and establishes relationships which are translated to the output. This is achieved by instances of prior learning used to train the ANN. Time-series-based neural networks are a common practical application of machine learning and are widely used in dynamic systems. In this study, we used a focused time-delay neural network (FTDNN), which is well suited for time series prediction.[20] Time-delay neural networks (TDNNs) are multilayer neural networks that can classify patterns with shift-invariance, meaning that the classifier does not require explicit segmentation before classification. For a temporal pattern such as an ECG, the TDNN thus avoids having to determine the beginning and endpoints of each signal. TDNNs and FTDNNs have been used extensively in speech recognition applications which pose similar challenges to ECG.[21,22] The

objective of this study was thus to use the particular features of a FTDNN to accurately reconstruct the full 12-lead ECG from a reduced lead set.

Many possible combinations of the six different precordial leads are available when performing lead reconstruction. Studies that used only a single precordial lead reported that lead V2 showed the best performance.[6,14] In the current study, we wanted to reconstruct leads using the fewest precordial leads possible to achieve the lowest possible RMSE, and therefore we chose lead V2 based on its documented performance. Furthermore, we confirmed that V2 provides better performance by testing each precordial lead as an input parameter for the FTDNN on the Physiobank's Pysikalisch-Technische Bundensanstalt (PTB) diagnostic ECG database and calculating the resulting RMSE and Pearson r values. The input to the neural network was recorded from electrodes located on the limbs as well as precordial lead V2. The limb electrodes RA, LA, LL (where RL facilitates the reference lead used in the right leg drive circuit) in combination with the relevant mathematical equations enabled the derivation of the bipolar limb leads (I, II, III) and unipolar limb leads (aVR, aVL and aVF). These leads were chosen due to the ease of placement. The bipolar limb leads, augmented unipolar limb leads and V2 were used as inputs to the neural network, which produced the remaining leads (V1 and V3-V6) as the output. The use of limb leads allowed for slight variability in the electrode placement and minimised the use of precordial electrodes which require significant precision. Small displacement of the precordial electrodes has been shown to have a much more significant influence on the measured ECG signal due to their close proximity to the heart compared to limb leads.[23,24] In addition, situations arise where the precordial electrodes need to be shifted or removed in order to administer bandages, drains as well as perform recordings with other medical devices such as echocardiograms.[15] However, deviations in ECG electrode placement from the correct 'standard' position[25] can also result from errors made by trained medical staff.[23,26-28] Therefore, a notable drawback is poor reproducibility of precordial lead placement, which results in high variability in the data obtained via ECG recordings.[29] Kerwin et al.[30] reported that lead placements with an error of less than 1 cm were attained by trained medical staff in only 50% of male patients and 20% of female patients. It has been reported that these placement errors are frequently in the range of between 2 and 3 cm, with some cases recording errors of up to 6 cm. Bond et al.[31] reported that incorrect electrode placement contributes to incorrectly diagnosing cardiovascular disease in 17-24% of cases by either human or computer-based analysis.[32] An ECG system with simple electrode placement could therefore potentially be used outside the professional environment, and potentially provide opportunities for use in rural locations by ordinary individuals as opposed to trained clinicians in hospitals.

METHODS

This study used the PTB diagnostic ECG database, which is an archived ECG database created by the National Metrology Institute of Germany for research and academic purposes. The ECG data were recorded from both healthy individuals and patients with cardiovascular disease at the Department of Cardiology of the University Clinic Benjamin Franklin in Berlin Germany. An ECG prototype recorder was used with a summary of the specifications presented in Table 1.

The PTB database consists of 549 recordings from 290 individuals between the ages of 17 and 87 years, with a mean age of 57.2 years. Of the total 290 individuals recorded, 209 were male (mean age 55.5 years) and 81 were female (mean age 61.6 years). Each recording consists of a standard 12-lead ECG as well as a Frank 3-lead VCG. However, for this study, only the standard 12-lead ECG recordings were analysed.[33] All ECG record-

Table 1. ECG prototype specifications

	PTB ECG prototype
Channels	16 channels (14 ECG, 1 respiration, 1 line voltage)
Input voltage	± 16 mv with ± 300 mv compensated offset voltage
Input resistance	100 Ω
Resolution	16 bit, 0.5 μV/LSB with 2000 A/D units per mV
Bandwidth	0-1 kHz synchronous sampling
Noise	10 μV (pp) max, 3 μV RMS with input short circuit

ECG, electrocardiogram; LSB, least significant bit; PTB, Physiobank's Pysikalisch-Technische Bundensanstalt.

ings were filtered with a digital band-pass filter with a bandwidth of 0.05-150 Hz to remove noise and baseline drift. This filter was designed to adhere to standards set by the American Heart Association (AHA).[25] After filtering, recordings that still contained significant artefacts were excluded. Recordings from patients that were below the age of 18 years or had missing information, as well as recordings taken on the same day, were also excluded from the study. The data exclusion process is shown in Figure 1. The included population was divided into subgroups based on their current cardiovascular condition (Table 2). These data were used to train, test and validate the neural network.

The task of prediction was to formulate a nonlinear function f that was capable of predicting values for $y(t)$ from previous values of $x(t)$, without prior values of $y(t)$. The model could thusbe characterised as:

$$y(t) = f\,(x(t-1),\ldots,\, x(t-d) \qquad (1)$$

where d is the system's input tap delay.[20] A FTDNN was

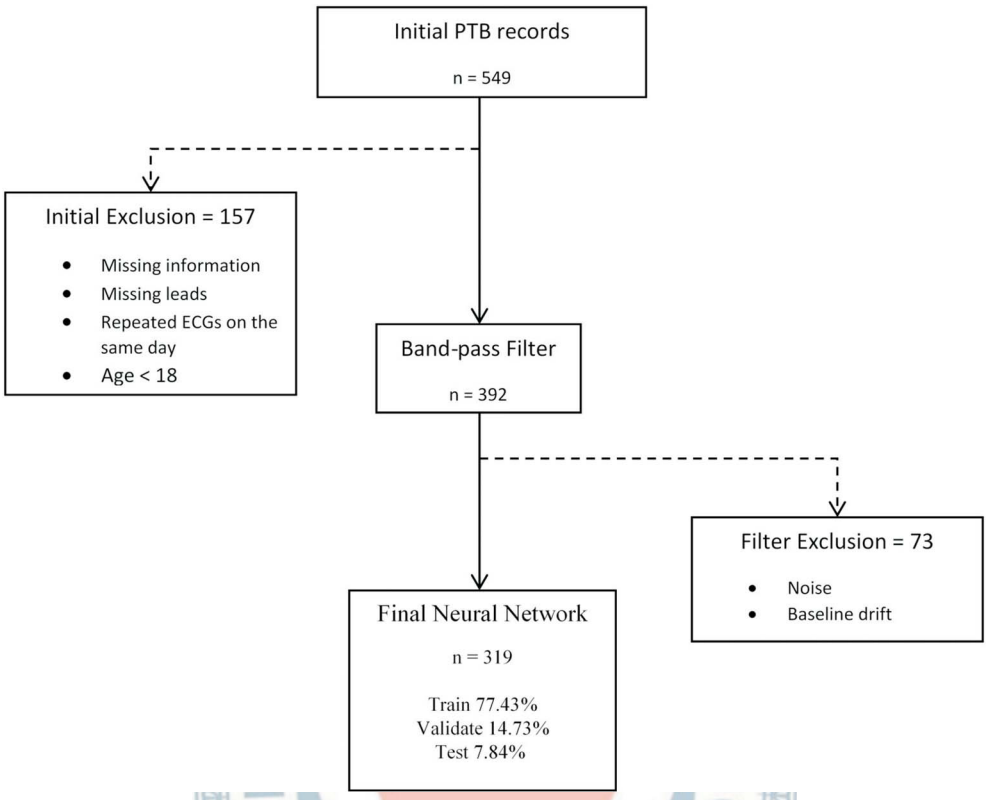

Figure 1. *Flow diagram indicating the exclusion process as well the procedure taken to reach the final neural network. PTB, Physiobank's Pysikalisch-Technische Bundensanstalt.*

Table 2. A summary of the included population's allocation to the training, validation and test categories

	Included population			
	Total n	Train n (% of total)	Validate n (% of total)	Test n (% of total)
Bundle branch block (BBB)	9	5 (55.56)	2 (22.22)	2 (22.22)
Cardiomyopathy (CM)	17	10 (58.82)	4 (23.53)	3 (17.65)
Dysrhythmia (D)	6	4 (66.67)	1 (16.67)	1 (16.67)
Healthy controls (HC)	41	27 (65.85)	8 (19.51)	6 (14.63)
Myocarditis (M)	3	2 (66.67)	0 (0)	1 (33.33)
Myocardial hypertrophy (MH)	5	3 (60)	1 (20)	1 (20)
Myocardial infarction (MI)	234	194 (82.91)	30 (12.82)	10 (4.27)
Valvular heart disease (VHD)	4	2 (50)	1 (25)	1 (25)
Total	319	247 (77.43)	47 (14.73)	25 (7.84)

constructed to calculate the time series values for leads V1 and V3-V6, given leads I, II, III, aVL, aVR, aVF and V2. The neural network was trained using past values of both $y(t)$, consisting of leads V1 and V3-V6, and $x(t)$, consisting of leads I, II, III, aVL, aVR, aVF and V2, where $y(t)$ is the desired output of the network and $x(t)$ is the input provided to the network. The layout of the neural network is shown in Figure 2.

The network could be described as a feedforward network consisting of a single hidden layer. The activation functions used for the hidden layer (f_1) and output layer (f_2) were the tan-sigmoid transfer function and linear transfer function, respectively. Ten neurons were used in the hidden layer, as this was found to be the optimal number during network training. Regularisation was implemented to mitigate the risk of overfitting, and less than 10 resulted in underfitting and more than 10 also resulted in exponentially increased processing time, lowering the time performance of the network significantly. The tapped delay line d was used to store prior values of up to two timesteps for the input $x(t)$ sequences. Bias values b_1 and b_2 were used to shift the activation functions to the left or right. The Levenberg-Marquardt algorithm was used, in which training concluded when the validation error failed to decrease for six iterations.[20] The ECG records for each subgroup were divided into training, validation and test sets, and each of the three sets contained healthy subjects as well as records from all the different CVD diseases available from the database (seen in Table 2). The ECG leads where normalised to fall within the range [-1, 1] before training the neural network, and later this process was reversed to obtain the true outputted values. The performance of the network was analysed using correlation and RMSE analysis between the reconstructed leads and the actual recorded values.

RESULTS

After the exclusion process, 319 cases were included in the study out of a total of 549 available cases in the PTB database. The characteristics of the cases are shown in Table 3. Analysis of the results showed five outliers out of the 25 records that made up the total test population. These consisted of two bundle branch block, one cardiomyopathy and two myocardial infarction records. Subjects with any lead that contained negative correlation values, $p > 0.05$ and RMSE > 500 μV, were identified as outliers.

The average Pearson r and RMSE values of the different disease subgroups and the various derived ECG leads are shown in Table 4 to Table 7 and are divided into the test population both including and excluding outliers. The leads used as inputs to the FTDNN were omitted as they are used to derive the remaining leads and were therefore without errors and exhibited perfect correlations ($r = 1.00$). The percentage correlation values were found to be equivalent to the Pearson r values in Table 4 to Table 7 for up to three decimal places, which was used as an indication of correlation by Tsouri as well as Tsouri and Ostertag.[11,12] The results for the test population including outliers across the reconstructed leads for all cases showed correlation values ranging from 0.8582 to 0.9705, and RMSE values of between 124 and 313 μV. The test population excluding outliers showed

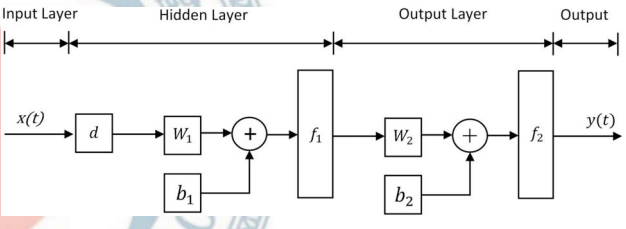

Figure 2. *The FTDNN layout.*

Table 3. Total population statistics

Population statistics	
n	319
Male (%)	71.16
Female (%)	28.84
Median age (all)	55 ± 13.2
Median age (male)	53 ± 12.8
Median age (female)	62 ± 13.4
Minimum age	22
Maximum age	86
Bundle branch block	9
Cardiomyopathy	17
Dysrhythmia	6
Healthy control	41
Myocarditis	3
Myocardial hypertrophy	5
Myocardial infarction	234
Valvular heart disease	4

Table 4. Population correlation including outliers

Pearson *r*	n	V1	V3	V4	V5	V6
All cases	25	0.9705	0.9447	0.8567	0.8582	0.8844
Bundle branch block	2	0.9763	0.9295	0.9270	0.8091	0.7702
Cardiomyopathy	3	0.9819	0.8977	0.7831	0.8736	0.7970
Dysrhythmia	1	0.8567	0.7607	0.7932	0.8802	0.9072
Healthy control	6	0.9678	0.9809	0.9246	0.9719	0.9674
Myocarditis	1	0.9859	0.9115	0.7902	0.9295	0.8952
Myocardial hypertrophy	1	0.9934	0.9768	0.8846	0.9583	0.9833
Myocardial infarction	10	0.9763	0.9643	0.8474	0.7843	0.8737
Valvular heart disease	1	0.9564	0.9252	0.7922	0.8875	0.9341

Table 5. Population correlation excluding outliers

Pearson *r*	n	V1	V3	V4	V5	V6
All cases	20	0.9678	0.9436	0.8609	0.9140	0.9204
Bundle branch block	-	-	-	-	-	-
Cardiomyopathy	2	0.9821	0.8580	0.7055	0.9188	0.9562
Dysrhythmia	1	0.8567	0.7607	0.7932	0.8802	0.9072
Healthy control	6	0.9678	0.9809	0.9246	0.9719	0.9674
Myocarditis	1	0.9859	0.9115	0.7902	0.9295	0.8952
Myocardial hypertrophy	1	0.9934	0.9768	0.8846	0.9583	0.9833
Myocardial infarction	8	0.9739	0.9666	0.8829	0.8766	0.8773
Valvular heart disease	1	0.9564	0.9252	0.7922	0.8875	0.9341

Table 6. Population RMSE including outliers

RMSE	n	V1	V3	V4	V5	V6
All cases	25	124	236	313	250	156
Bundle branch block	2	176	525	671	583	290
Cardiomyopathy	3	194	387	555	336	158
Dysrhythmia	1	92	177	271	316	343
Healthy control	6	97	167	240	157	158
Myocarditis	1	71	158	297	339	201
Myocardial hypertrophy	1	145	87	199	356	209
Myocardial infarction	10	94	193	229	179	101
Valvular heart disease	1	297	256	241	236	148

Table 7. Population RMSE excluding outliers

RMSE	n	V1	V3	V4	V5	V6
All cases	20	123	176	245	182	140
Bundle branch block	-	-	-	-	-	-
Cardiomyopathy	2	241	352	450	187	142
Dysrhythmia	1	92	177	271	316	343
Healthy control	6	97	167	240	157	158
Myocarditis	1	71	158	297	339	201
Myocardial hypertrophy	1	145	87	199	356	209
Myocardial infarction	8	95	141	195	133	86
Valvular heart disease	1	297	256	241	236	148

correlation values ranging from 0.8609 to 0.9678, and RMSE values between 123 and 245 μV for all cases, across the reconstructed leads. All correlations, except one outlier, were statistically significant at $p < 0.01$.

Figure 3 was adapted from Schrek and Fishberg,[6] in which the RMSE analyses for the non-linear optimisation method (NLO), EASI leads method, Mason-Likar method and FTDNN method were plotted for the various leads and compared on the same set of axes. The NLO and FTDNN methods exhibited zero RMSE for the leads (I, II, III, aVR, aVL, aVF and V2) used as inputs to reconstruct the remaining leads. Figure 4 displays a comparison between the derived signal using the FTDNN method and the recorded signal for a 12-lead ECG of healthy controls from the test set.

DISCUSSION

This retrospective study is the first ANN study, or more specifically a FTDNN study, to uses limb leads and lead V2 as the input to the network to reconstruct the

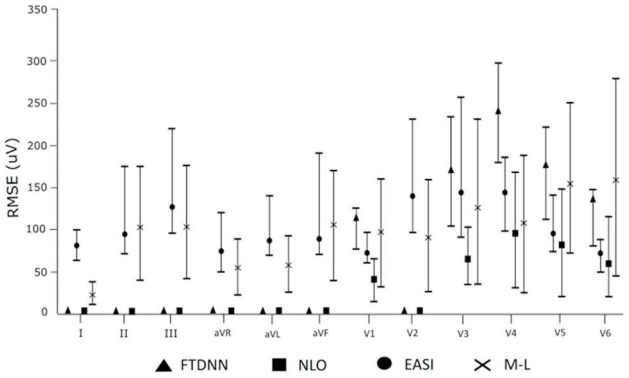

Figure 3. *Comparison of the RMSE analysis for several reconstruction methods. The graph was adapted from Schrek and Fishberg[6] and compares the RMSE ± SD NLO 12-lead ECG derivation method and the Mason-Likar method, as well as the RMSE and interquartile range for the reported EASI and the FTDNN methods. ECG, electrocardiogram; FTDNN, focus time-delay neural network; NLO, non-linear optimisation method; RMSE, root mean square error; SD, standard deviation.*

missing precordial leads. The FTDNN resulted in the reconstruction of the full 12-lead ECG with Pearson *r* correlations for the test population including outliers ranging from 0.7607 to 0.9934, and RMSE values between 71 and 671 μV, with only one lead identified as not being statistically significant across all cardiovascular diseases.

In the case of the test population excluding outliers, the lower bound of the range of Pearson *r* correlations decreased to 0.7055 and the upper bound remained at 0.9934, however the average across all cases increased significantly. In the case of the RMSE values, the lower bound for the population excluding outliers remained unchanged at 71 μV, however the upper bound decreased significantly to 450 μV, and the average across all leads also decreased significantly. All leads were statistically significant ($p < 0.01$) across all cardiovascular diseases. Both the correlation and RMSE values in Table 4 to Table 7 as well as Figure 3 show that the reconstructed leads were comparable with previous methods. Lead V4 was the weakest reconstructed lead by the FTDNN method, exhibiting higher RMSE values in comparison with the other methods. After analysing the removed outliers, the FTDNN method failed to accurately reconstruct those with bundle branch block cardiovascular disease. With only a small sample size of cardiovascular diseases available to train the neural network, further data are required in order to confidently verify this finding.

The NLO study done by Schreck et al. (2002)[18] used the PTB database as well as one additional database.

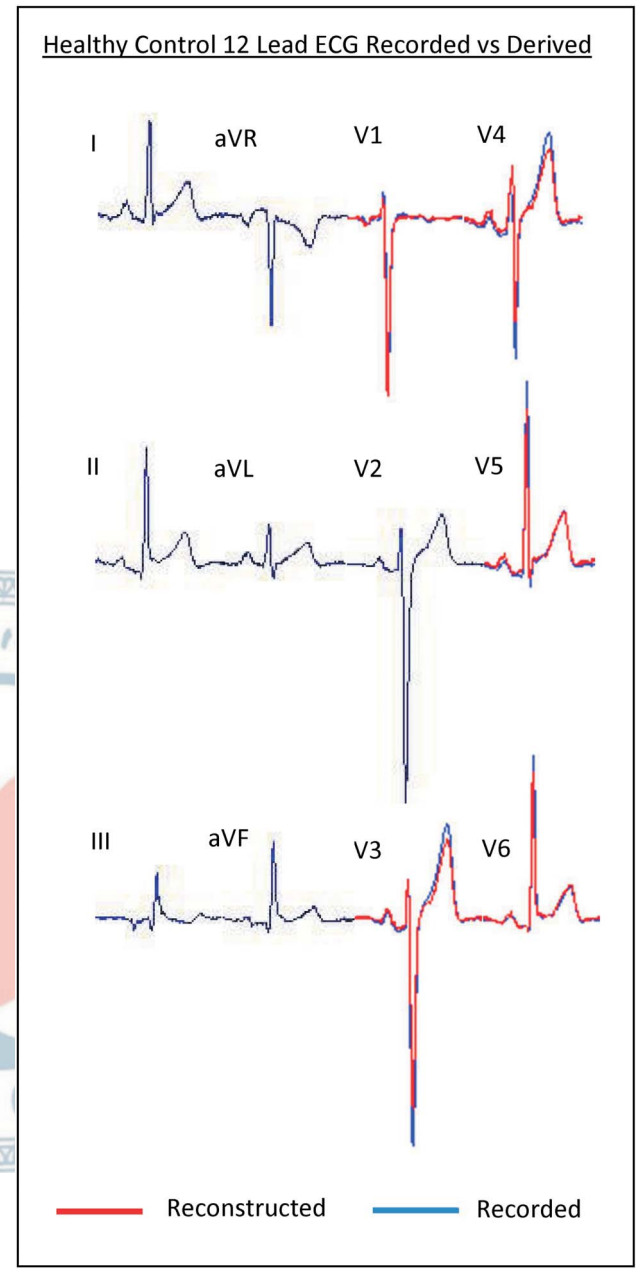

Figure 4. *A 12-lead electrocardiogram (ECG) of a healthy control indicating the reconstructed signal (red) vs. the recorded signal (blue).*

The same leads were used as basis leads for the reconstruction of the absent five precordial leads (V1, V3-V6). The Pearson *r* correlation for leads V1, V3-V6 for all cases was 0.71-0.90, which was slightly weaker compared with the current study. However, the RMSE values of the NLO method were lower and compared favourably to those of the EASI leads, M-L and the current study FTDNN reconstruction method on the same set of

axes, as seen in Figure 3.

Tsouri and Ostertag[12] used the same PTB database and showed high correlations between the reconstructed leads and the actual lead values with an average percentage correlation value of 96.9-97.9% for leads III, aVR, aVL and aVF, and 92.8-96.3% for V1, V3, V4, V5 and V6 after 30 seconds. The Pearson *r* correlation values in the current FTDNN study are shown in Table 4 and Table 5, and they were equivalent to the percentage correlation used by Tsouri and Ostertag for up to three decimal places. Therefore, the current study compares less favourably to that of Tsouri and Ostertag.[12] However, it is important to note that the FTDNN did not require past values of all 12 leads for each patient, whereas Tsouri and Ostertag required a calibration period in which data from all the leads were required before missing leads could be reconstructed. This would not be appropriate in situations in which only reduced lead ECGs were available. Specialists trained in placing the full 12-lead ECG would also be required to place the initial leads before they were removed, which is not desirable.

The EASI lead study performed by Nelwan et al.[10] used nonstandard lead placements based on the Frank leads to derive the 12-lead ECG. However, using an unconventional lead placement system resulted in inherent electrode placement variability within all leads.[34] The FTDNN performed slightly less favourably in comparison with the EASI lead method with respect to RMSE, however the EASI study consisted of only 44 male subjects all of whom required a percutaneous coronary intervention procedure. This limited the range of tested cardiovascular diseases to men with acute coronary syndromes. The clinical value of the VCG and the Frank lead system is well documented, however, since its inception 50 years ago, the method has become obsolete. This is due to the lack of existing education on the technology, placement and equipment. In contrast, the current study as well as Schreck and Fishberg's[6] used standard limb leads and V2, which are a subset of conventional 12-lead ECG.

Drew et al.[9] performed an M-L study which also used non-conventional lead placement for two leads located in the vicinity of traditional leads V3 and V4. The FTDNN performed similar to the M-L method for leads V1-V5, with slightly higher mean values but lower standard deviations in the reconstructed leads. The FTDNN reconstructed lead V6 had a lower mean value and better standard deviation (Figure 3). The M-L validation study reconstructed leads for prehospital ST-segment monitoring, limiting the focus of the study to cardiac rhythm, prior infarction, ST/T wave changes and acute myocardial ischemia.

The only other known neural network study was done by Prauzek et al.,[7] in which various combinations of precordial leads as inputs were used to reconstruct the remaining absent precordial leads, with limited success. Focus was placed solely on the precordial leads which were reconstructed using neural networks which used different combinations of V1, V2 and V6 as inputs and reconstructed the remaining precordial leads as outputs. However, the reduced lead subset used in the current study is preferrable, as one precordial lead (V2) was required in the reconstruction of the 12-lead ECG compared to the three precordial leads required by Prauzek et al.[7] In addition, the use of simple lead placement of the limb leads (I-III, aVR, aVL and aVF) obtained from the limb electrodes could provide additional views of the heart without the need for complex or obstructive electrode placement. These additional leads increased the probability of obtaining an accurate lead reconstruction.

The current study has several strengths. The ECG recordings were conducted by a medical doctor in a clinical environment. The PTB database used in this study is trusted and has been used in several prior studies done within the field of research. The data were pre-processed using a band-pass filter that adheres to recommendations set by the AHA. A large training population consisting of 247 cases was included in the study and subsequently used to train the neural network. The population exhibited great diversity with male and female patients aged 22-86 years, and included several disease subgroups in which the FTDNN network could accurately reconstruct. In terms of correlation, the FTDNN network compared favourably to known lead reconstruction methods. With respect to RMSE, the current study produced similar results to known lead reconstruction methods, although lead V4 exhibited slightly weaker RMSE values. Finally, this study used standard lead positions that relied less on precordial leads, using information available from the limb leads which are less sensitive to variability. As this is a retrospective study, several sources of bias exist that can be identified as limitations. Although

the ECG recordings were conducted by a medical doctor, precordial lead placement inherently has high variability which may have affected the results. The ECG recordings were acquired from a single database which increases the possibility of random errors and spectrum bias. A large amount of the available data was required to train the neural network in such a manner as to include all the disease subgroups and ensure the network was fully represented. This resulted in a small percent (7.84%) of the total cases being available for testing the neural network, which is significantly less than alternative reconstruction methods and may have led to selection bias. In the EASI lead study, the derived leads calculated by the early implementation of the EASI method differed notably from the original leads. This was believed to be a result of deriving the transformation coefficients from a limited dataset. Work done by Feild et al.[14] aimed to improve on the accuracy of the 12-lead ECG reconstruction. This was achieved by calculating a new set of EASI lead transformation coefficients from additional data acquired from two ECG databases. The two databases consisted of 892 and 91 ECG records, respectively. Nelwan et al.[10] used the improved EASI lead coefficients, testing the method on 44 subjects. In comparison, we used 319 training subjects and 45 validation subjects to construct the neural network model, and tested this model on 25 subjects. The limited amount of available data used by the current study may explain why the method performed slightly less favourably than the established reconstruction methods (Figure 3) in addition to the failure to accurately reconstruct diseases with less available training data, such as bundle branch block. This also indicates the potential for improvement and optimisation of the FTDNN method, or ANN methods in general, by acquiring larger datasets used in the training procedure.

The FTDNN took advantage of the widespread redundancy expressed throughout the precordial leads. The network was able to accurately identify non-linear relationships between the input and output leads, resulting in the accurate calculation of the numerous neuron weights and bias values required to reconstruct the missing leads. It is important to note that the network could only accurately predict the output of cardiovascular diseases present in the population used to train the neural network. Therefore, new cardiovascular diseases not present in the training population or diseases that display highly variable waveform structures would not be reproduced accurately. Additionally, waveforms that are not repetitive in nature and exhibit sudden deviation from a sequence would not be reconstructed accurately, as seen in Figure 5.

CONCLUSION

In conclusion, the FTDNN successfully reconstructed V1 and V3-V6 from input leads I, II, III, aVL, aVR, aVF and V2. The results obtained excluding outliers indicated high correlations that were statistically significant and low RMSEs for both the healthy controls and the disease subgroups, except those in the bundle branch block disease subgroup. This may be due to the high levels of redundancy that exist primarily in precordial leads. This could lead to further research in ECG lead reduction and possibly novel methods to diagnose cardiovascular dis-

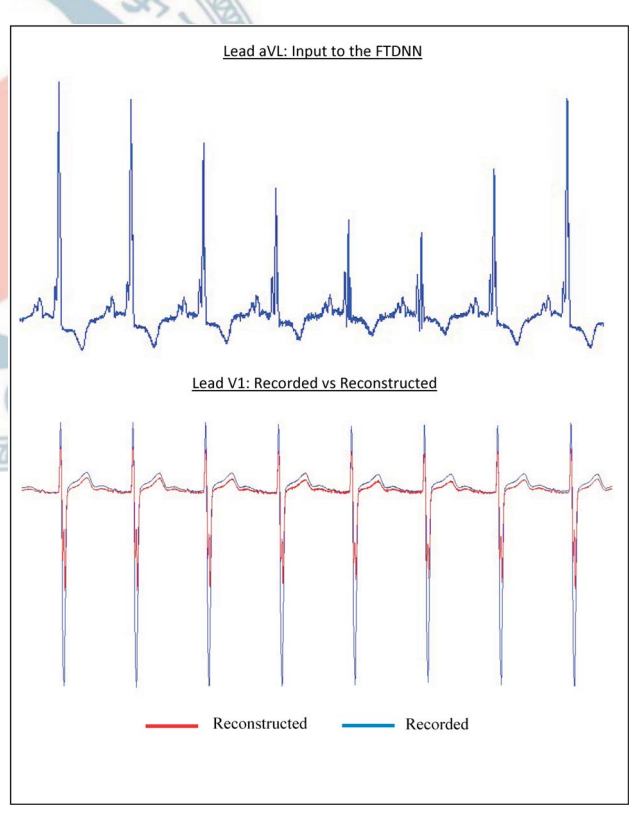

Figure 5. *Indication of the effect of irregular inputs to the focus time-delay neural network (FTDNN) and its consequence on the reconstructed output. Lead aVL from a subject diagnosed with valvular heart disease used as an input to the FTDNN network as well as the corresponding recorded signal and the reconstructed signal of V3.*

eases that are simple to execute, resulting in improved accuracy and patient comfort. Lo et al.[35] reported that a wearable ECG device is ready for clinical use with an accuracy comparable to standard 12-lead ECG systems. The medical relevance of this study is the potential to use a reduced lead set to reconstruct the traditional full 12-lead ECG that is trusted by cardiologists and healthcare specialists when diagnosing cardiovascular diseases and during patient monitoring. The use of five electrodes of which four are limb leads will be less sensitive to errors in electrode placement and will allow for its use in rural applications by nurses or trained individuals compared to the standard 12-lead ECG which requires specialists in a clinical environment. Fewer leads will also be more comfortable for patients undergoing long-term monitoring and will be easier and less time consuming to apply. Overall, the technology will be more accessible and readily available for the general population. This study will contribute to further discussions involving 12-lead ECG as being the gold standard, the possibility for further lead reduction, the existence of redundancy in precordial leads as well as the methods in which cardiovascular diseases are diagnosed. The immediate future focus of this research will be to validate the FTDNN with larger datasets, the acquisition of which is currently the primary focus. Further future work will also entail focusing on the limitations of this study which can be addressed by gathering data from multiple databases consisting of healthy controls and subjects with cardiovascular diseases. These data will be used to further train and test the FTDNN and further expand the network's exposure to more pathologies as well as improve the reconstruction of the current existing pathologies. Additionally, an FTDNN could be embedded on a device and used to actively reconstruct the full 12-lead ECG in real time.

ACKNOWLEDGEMENTS

This research was partially funded by the South African National Research Foundation.

CONFLICTS OF INTEREST

All the authors declare no conflict of interest.

REFERENCES

1. Burger HC, Van Milaan J. Heart-vector and leads. *Br Heart J* 1946; 8:157.
2. McFee R, Parungao A. An orthogonal lead system for clinical electrocardiography. *Am Heart J* 1961;62:93-100.
3. Schmitt OH, Simonson E. Symposium on electrocardiography and vectorcardiography: the present status of vectorcardiography. *AMA Arch Intern Med* 1955;96:574-90.
4. Frank E. An accurate, clinically practical system for spatial vectorcardiography. *Circulation* 1956;13:737-49.
5. Dawson D, Yang H, Malshe M, et al. Linear affine transformations between 3-lead (Frank XYZ leads) cectorcardiogram and 12-lead electrocardiogram signals. *J Electrocardiol* 2009;42:622-30.
6. Schreck DM, Fishberg RD. Derivation of the 12-lead electrocardiogram and 3-lead vectorcardiogram. *Am J Emerg Med* 2013; 31:1183-90.
7. Prauzek M, Peterek T, Penhaker M. Reduction of ECG precordial leads. *Conf Proc IEEE Int Conf Sign Proc Syst (ICSPS)* 2010;1:V1-354.
8. Sejersten M, Pahlm O, Pettersson J, et al. The relative accuracies of ECG precordial lead waveforms derived from EASI leads and those acquired from paramedic applied standard leads. *J Electrocardiol* 2003;36:179-85.
9. Drew BJ, Dempsey ED, Joo TH, et al. Pre-hospital synthesized 12-lead ECG ischemia monitoring with trans-telephonic transmission in acute coronary syndromes: pilot study results of the ST SMART trial. *J Electrocardiol* 2004;37:214-21.
10. Nelwan SP, Kors JA, Crater SW, et al. Simultaneous comparison of 3 derived 12-lead electrocardiograms with standard electrocardiogram at rest and during percutaneous coronary occlusion. *J Electrocardiol* 2008;41:230-7.
11. Ostertag MH, Tsouri GR. Reconstructing ECG precordial leads from a reduced lead set using independent component analysis. *Conf Proc IEEE Eng Med Biol Soc* 2011:4412-7.
12. Tsouri GR, Ostertag MH. Patient-specific 12-lead ECG reconstruction from sparse electrodes using independent component analysis. *IEEE J Biomed Health* 2014;18:476-82.
13. Dower GE, Machado HB, Osborne JA. On deriving the electrocardiogram from vectoradiographic leads. *Clin Cardiol* 1980;3:87-95.
14. Feild DQ, Feldman CL, Horacek BM. Improved EASI coefficients: their derivation, values, and performance. *J Electrocardiol* 2002; 35:23-33.
15. Nelwan SP, Kors JA, Meij SH, et al. Reconstruction of the 12-lead electrocardiogram from reduced lead sets. *J Electrocardiol* 2004; 37:11-8.
16. Schijvenaars B. Intra-individual variability of the electrocardiogram: assessment and exploitation in computerized ECG analysis. *Erasmus University Rotterdam thesis*, 2000.
17. Feild DQ, Zhou SH, Helfenbein ED, et al. Technical challenges and future directions in lead reconstruction for reduced-lead sys-

tems. *J Electrocardiol* 2008;41:466-73.
18. Schreck DM, Brotea C, Shah S. Derivation of the 12-lead electrocardiogram using abstract factor analysis and simplex optimization. *Int J Bioelectromagn* 2002;4:337-8.
19. Russell SJ, Norvig P, Canny JF, et al. Artificial intelligence: a modern approach (Vol. 2). Upper Saddle River: Prentice Hall, 2003.
20. Beale MH, Hagan MT, Demuth HB. Neural network toolbox™ User's Guide. In R2016b, The MathWorks, Inc., 3 Apple Hill Drive Natick, MA 01760-2098, 2001.
21. Peddinti V, Povey D, Khudanpur S. A time delay neural network architecture for efficient modeling of long temporal contexts. *INTERSPEECH* 2015.
22. Snyder D, Garcia-Romero D, Povey D. Time delay deep neural network-based universal background models for speaker recognition. *IEEE Workshop on Automatic Speech Recognition and Understanding*, Scottsdale, 2015.
23. Rajaganeshan R, Ludlam CL, Francis DP, et al. Accuracy in ECG lead placement among technicians, nurses, general physicians and cardiologists. *Int J Clin Pract* 2008;62:65-70.
24. Van Oosterom A, Hoekema R, Uijen GJH. Geometrical factors affecting the interindividual variability of the ECG and the VCG. *J Electrocardiol* 2000;33:219-27.
25. Kligfield P, Gettes LS, Bailey JJ, et al. Recommendations for the standardization and interpretation of the electrocardiogram: part I: the electrocardiogram and its technology a scientific statement from the American Heart Association Electrocardiography and Arrhythmias Committee, Council on Clinical Cardiology; the American College of Cardiology Foundation; and the Heart Rhythm Society endorsed by the International Society for Computerized Electrocardiology. *J Am Coll Cardiol* 2007;49:1109-27.
26. Herman MV, Ingram DA, Levy JA, et al. Variability of electrocardiographic precordial lead placement: a method to improve accuracy and reliability. *Clin Cardiol* 1991;14:469-76.
27. McCann K, Holdgate A, Mahammad R, Waddington A. Accuracy of ECG electrode placement by emergency department clinicians. *Emerg Med Australas* 2007;19:442-8.
28. Rudiger A, Hellermann JP, Mukherjee R, et al. Electrocardiographic artifacts due to electrode misplacement and their frequency in different clinical settings. *Am J Emerg Med* 2007;25:174-8.
29. Kania M, Rix H, Fereniec M, et al. The effect of precordial lead displacement on ECG morphology. *Med Biol Eng Comput* 2014;52:109-19.
30. Kerwin AJ, McLean R, Tegelaar H. A method for the accurate placement of chest electrodes in the taking of serial electrocardiographic tracings. *Can Med Assoc J* 1960;82:258.
31. Bond RR, Finlay DD, Nugent CD, et al. The effects of electrode misplacement on clinicians' interpretation of the standard 12-lead electrocardiogram. *Eur J Intern Med* 2012;23:610-5.
32. Schijvenaars BJ, Kors JA, van Herpen G, et al. Effect of electrode positioning on ECG interpretation by computer. *J Electrocardiol* 1997;30:247-56.
33. Goldberger AL, Amaral LA, Glass L, et al. Physiobank, physiotoolkit, and physionet components of a new research resource for complex physiologic signals. *Circulation* 2000;101:e215-20.
34. Saghiri MA, Asgar K, Boukani KK, et al. A new approach for locating the minor apical foramen using an artificial neural network. *Int Endod J* 2012;45:257-65.
35. Lo C, Chang S, Tsai J, et al. Evaluation of the accuracy of ECG captured by CardioChip through comparison of lead I recording to a standard 12-lead ECG recording device. *Acta Cardiol Sin* 2018;34:144-51.