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Deep neural network based missing data prediction of electrocardiogram signal using multiagent reinforcement learning

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A R T I C L E I N F O

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A B S T R A C T

Objective: Clinical morphology of electrocardiogram (ECG) signal is compulsory to analyze the cardiac activity. During long term measurement, missing of data is a common factor, caused by sensor loosening, resulting in devastating feature extraction procedure; hence, prediction of those missing data is indispensable.
Methods: In this work, bidirectional long short-term memory recurrent neural network (LSTM-RNN) based prediction of missing segment of ECG signal is accomplished, governed by reinforcement learning (RL) using multiagent. The LSTM-RNN has internal gate architecture, which can predict the upcoming sequence using the past features of ECG. Each agent of the multiagent system (MAS), which represents various fictitious domain of ECG, has independent learning module to predict respective domain using a 'critic' network, which was conducted by a multilayer perceptron neural network (MLPNN). The MAS finally predicted the missing segment by 'cooperative learning' algorithm using a 'coordinator agent'.
Results: The proposed algorithm was tested on MIMIC-II ECG database, available in Physionet. Experimental result shows that, using the RL, the trained LSTM-RNN was able to predict the missing segments more precisely with correlation coefficient higher than 0.9 and low root mean squared error.
Conclusion: The proposed method is applicable to any single channel ECG signal, and the quality of predicted signal ensures a wide application in medical applications as well as telecardiology system.
Significance: A comparative study with previously published works showed an improved performance, related to ECG missing data prediction, implemented on MIMIC-II records.

1. Introduction

1.1. Overview and motivation

Electrocardiogram (ECG) signal is one of the most vital bioelectric signals [1] that is generated due to periodic contraction and expansion of heart muscle. ECG plays a crucial role, while detecting various cardiovascular diseases and heart abnormalities by classifying features of various fictitious characteristics. By placing electrodes at specific positions on human boy, ECG is calibrated as potential difference of those electrodes, after being the signal is conditioned (noise removal, amplification etc.). A 'beat' is the main repeated part of ECG which makes it a periodic signal. Long term ECG recording is generally performed in ICUs for continuous health monitoring purpose.

Mainly two types of problem arise, while long term ECG recording is conducted viz. 1) missing of particular segment due to sudden loosening of electrodes, and 2) corruption due to motion artifact and interference of various noise or equipment behavior. Due to these above-mentioned facts, the general pattern of ECG is hampered resulting in wrong calibration and missing of important clinical features. Therefore, detection of this missing /corrupted segments along with prediction of those segment has become a challenging work for decades. Being a periodic signal, feature extraction or pattern reorganization becomes easy for ECG signal. Now, this prediction can be performed by pattern classification in time domain using linear prediction [2], template matching [3]. In this category, missing or corrupted signals are predicted by linear computation using past samples so that the general pattern of ECG can be re-established within the missing segment. Another approach of prediction is based on feature extraction theory, in which various transformed domain techniques like PCA [4], and various transfer functions e.g. impulse response [5] are utilized to predict the missing pattern of the periodic signal. With the advancement of computational intelligence, a third category of data prediction is performed using machine learning, in which various neural network like feed forward

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neural network [6], recurrent neural network (RNN) [7] provided the good result. In addition, using entropy encoding [8], detection of missing segment and prediction by linear computation reduced the prediction error. Bayesian approach [9] of data prediction of missing physiological signal has provided an improved result. In recent works, long short-term memory recurrent neural network (LSTM-RNN) [10] has become a popular data prediction tool in various time-series forecasting applications like, healthcare [11], electrical load flow [12] etc. The LSTM-RNN has internal gate topology that keeps the information of past pattern of any time-series signal, and based on that, this network can also predict the upcoming pattern of that signal.

Now, while predicting any upcoming signal blindly, the changing behavior of environment or the upcoming pattern is generally unknown to any prediction technique. Thus, while predicting, response from the environment or accuracy of prediction should be knowledgeable to the mathematical tool, used for prediction. Reinforcement learning [13] is an iterative learning approach, in which, learning network receives a reward from the environment after each iteration, and based on that value, the network self-updates its response behavior to meet the desired goal [14]. A multiagent learning system possesses cooperative learning architecture with independent intelligence [15]. Implementation of multiagent based reinforcement learning provides an improved collective result to achieve an optimal and equilibrium response [16].

1.2. Contributions and paper organization

In all previously published works on ECG prediction theory, mainly based on features of clean pattern of the signal, missing segment was predicted blindly without keeping the track on accuracy of prediction in each step. In addition, an ECG beat has various fictitious domain e.g., P-wave, QRS complex etc., possessing independent feature; but while predicting, the entire beat was predicted as a whole, without restoring those independent features. In this work, therefore a new reinforcement learning based bidirectional LSTM-RNN was used to predict any missing segment of a periodic ECG signal. The main contributions are, 1) to introduce a new bidirectional LSTM-RNN based missing data prediction of single lead ECG. The bidirectional architecture assist to forecast the base line artifact, so that the predicted signal can best fit within the missing segment; 2) to categorize the ECG beats into various segments and treat each segment as an independent 'agent' to predict the entire missing segment in 'cooperative learning' process; 3) to introduce multiagent reinforcement learning process to improve the accuracy of prediction of trained RNN in each step; 4) to propose extrapolation and baseline matching using slope adjustment to align the predicted signal, perfectly at its two end within the missing segment.

The rest of the paper is organized as follows, Section 2 elaborates the proposed method of learning and prediction theory, Section 3 shows the experimental result implemented on MIMIC-II ECG database, Section 4 explains comparative study with previously published works on ECG data prediction and finally Section 5 concludes the inferences drawn from this work.

2. Material and methods

2.1. Information about database used for evaluation

The proposed algorithm was tested on MIMIC-II database available on Physionet [17]. The BIDMC or MIMIC-II database contains 53 records containing various physiological signals viz. photoplethysmogram (PPG), impedance respiratory (IR) signal, and electrocardiogram (ECG) signal, among which the ECG signal with 125 Hz sampling frequency, was selected for testing. These signals were recorded from 53 adult patients (among which 32 were female) with age limit between 19 and 90+ (mean age 64.81). The patients were admitted to medical and surgical intensive care units (ICU) at the Beth Israel Deaconess Medical Center (BIDMC), Boston, USA. Each recording was of 8-minute duration and was arbitrarily selected as the test set to generate this database. The original data were recorded from critically-ill patients at the hospital care, using pulse oximeter. The ECG signals were taken out from the MIMIC-II [18] matched waveform database and the breath annotations were added manually by annotators, using impedance respiratory signal. Among the 53 records, 44 single lead ECG records were used for beat delineation and missing data prediction purpose, mentioned below.

2.2. Signal processing flow

The signal processing flow diagram is shown in Fig. 1. The prediction algorithm was performed through 1) bidirectional LSTM-RNN (Bi-LRNN) and 2) multiagent reinforcement learning (MARL) approach. After detection of missing or corrupted segment, LSTM-RNN was trained using previous and preceding normal and clean ECG beats, in forward and backward approach respectively, to predict the missing segment pattern. Then, using reinforcement learning (RL), a blind prediction was performed during validation period, using reference signal (which is called 'forecasting') to update the network weights and generate another 'critic' network, so that the entire system was capable to predict the missing segment in varying environment, during testing period. Finally, prediction of missing segment was performed using these trained networks with the help of a 'coordinator agent', which effectuated the sample distribution and baseline alignment to fit the predicted signal within the missing segment of the original ECG. The various stages of data prediction procedure are explained below.

2.3. Beat delineation and agent formation

It was primary necessity to detect any missing or corrupted segment in single lead ECG. Therefore, proper ECG beat estimation was carried out by detecting the R-peaks using derivative based approach [19]. After detecting each R-peaks successfully, receptive beat estimation was accomplished using the following equation [20,21],

$$ {}_{k}R_{onset} = {}_{k}R - \left(0.33 \times {}_{k,k-1}\Delta R\right) $$

$$ {}_{k}R_{offset} = {}_{k}R + \left(0.67 \times {}_{k+1,k}\Delta R\right) \tag{1} $$

where ${}_{k}R_{onset}$ and ${}_{k}R_{offset}$ is the onset and offset of k^{th} R-peak, ${}_{k}R$ and ${}_{k1,k2}\Delta R$ represents the RR interval between $k1^{\text{th}}$ and $k2^{\text{th}}$ R-peak. Now, detection of missing segments was conducted using derivative based pattern recognition approach, because the general motif of a beat was hampered, if any missing or distorted segment was detected. For any missing segment, samples with constant values were obtained; and for corrupted signal, fluctuating values were detected which had a different pattern as compared to normal ECG beat. Thus, after detecting this missing segment, five normal ECG beats were chosen from each end of missing segment for the purpose of training the Bi-LRNN. Now, beat delineation was carried out using discrete wavelet transform (DWT) [22] to detect each fictitious segment of ECG beat [23]. The DWT decomposes an ECG beat into various frequency subbands, and therefore it becomes easier to detect the fictitious domains more precisely (pictorial representation of WT and beat delineation accuracy is provided in Section 3). Generally, the P-wave, T-wave, QRS complex become more distinguishable within 10–20 Hz frequency domain. Therefore, each ECG beat was decomposed into necessary frequency subband; e.g., in this work, the result analysis was performed using MIMIC-II ECG records (details of these database is explained in Section 3), which are sampled in 125 Hz data frequency. Therefore, each beat has undergone through third level of wavelet decomposition, and the reconstruction was done using approximate and first detailed coefficient, to detect the positions of P and T-peaks in the wavelet recomposed signal mentioned, as *pseudo-peaks*. Using these pseudo-peaks, accurate position of P and T-peaks, in the original beat, were estimated using sample-to-sample computation with minimum gradient or by detecting the slope inversion [24].

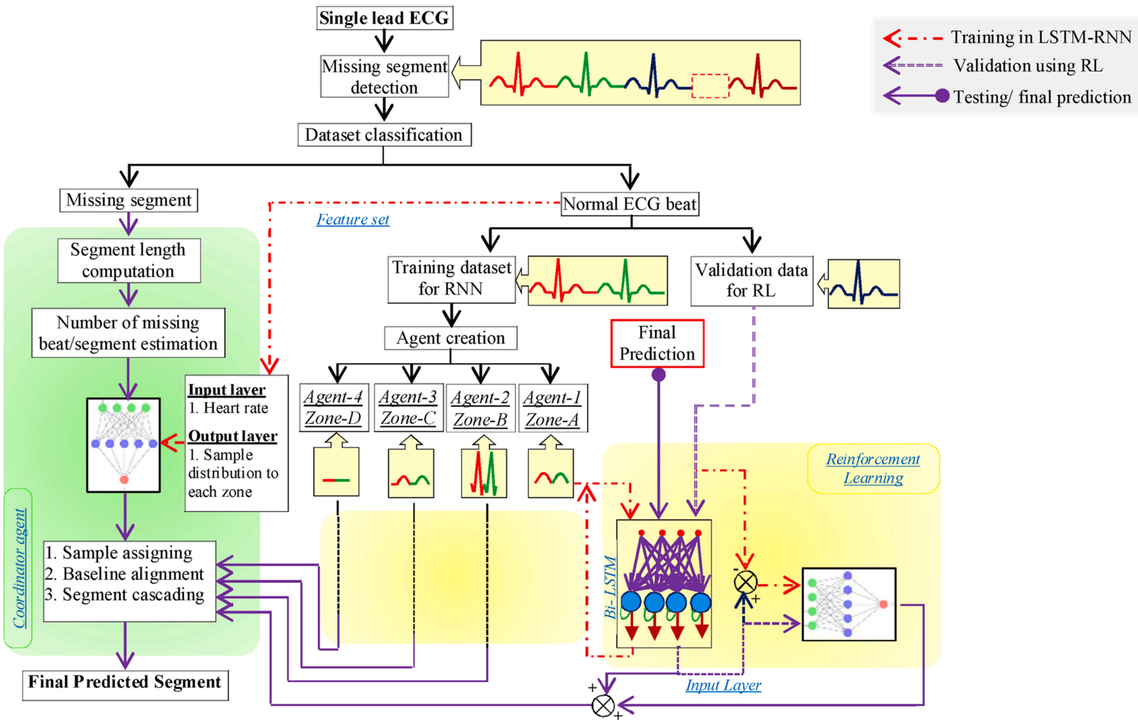


Fig. 1. Signal processing flow diagram of proposed work.

Now, a window of 90 millisecond (ms) was generated on either side (before and after) of R-peak, or the sample indices, where slope inversion occurred (on both sides), were marked as Q and S-peaks, before and after the R-peak, respectively. The next task was to estimate the onset and offset of P and T-waves. For this purpose, window of 70 ms for P-wave and 120 ms for T-wave, were generated on either side; and using the similar logic (minimum gradient or slope inversion), onset and offset of P and T-waves were estimated. In this way, segmentation of each beat was performed. Using these segments, four domains were created which were treated as four different agents. The four agents were 1) Zone-1: [P-wave], 2) Zone-2: [PQ-segment + QRS complex], 3) Zone-3: [ST-segment + T-wave], and 4) Zone-4: [TP-segment]. These agents were classified to train the Bi-LRNN during prediction. To previse those respective segments separately, prediction was performed more precisely using independent features. Thus, without training the entire beat at a time, four agents were used to predict the entire beat, in a combined approach, hence acted as multiagent. Now, these segments were used to train the Bi-LRNN as explained below.

2.4. Bi-LRNN architecture and training process

The LSTM-RNN was trained using forward and backward algorithm, so that the predicted segment could attain almost exact pattern of the missing segment. The recurrent neural network (RNN) is popular deep learning approach for prediction of any time-series data. It uses inherent memory stages [25], which are capable of storing the information about previous output and present input of reference data to predict the present output. Due to the presence of gradient vanishing and gradient exploding drawbacks, the function of traditional RNN is limited, when long term series prediction is performed. The LSTM-RNN incorporates internal gate architecture to predict the forthcoming sequences for a long-term data. The general block diagram of LSTM-RNN is shown in Fig. 2, which contains four basic gates viz. forget, input, update, and output gate. The updating of internal weights for training the network, was carried out using the following equations as,

$$f_t = \sigma\left(\omega_f[y_{t-1}, x_t] + b_f\right)$$

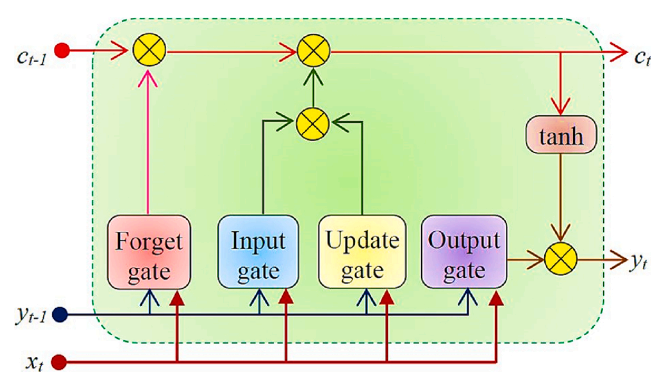


Fig. 2. Block diagram of LSTM recurrent neural network.

$$i_t = \sigma(\omega_i[y_{t-1}, x_t] + b_i)$$

$$c_t = \tanh(\omega_c[y_{t-1}, x_t] + b_c)$$

$$c_t = f_t{*}c_{t-1} + i_t{*}c_t$$

$$o_t = \sigma(\omega_o[y_{t-1}, x_t] + b_o) \tag{2}$$

The 'forget gate' (f_t) compares the current state input (x_t) with the previous state output (y_{t-1}), with the help of a sigmoid function 'σ(•)' to make decision about the amount of information to be accepted, to update internal weights (ω_f) using input bias value (b_f). Now, comparing current input state values with previous output responses, the 'input gate' (i_t) updates its weights (ω_i) using respective bias value (b_i). The 'update gate' (c_t) further updates its weights (ω_c) using the input gate information, with the help of a hyperbolic tangent operator 'tanh(•)' with update bias (b_c). Finally, the 'output gate' (o_t) controls the amount of information to be passed to present output state, by updating its own weights (ω_o) using sigmoid function and update bias (b_o), thus providing the final state output 'y_t' as follows,

$$y_t = o_t * \tanh(c_t) \quad (3)$$

Now, using this network architecture, training was executed using forward and backward approach, separately using separate training and validation dataset. For forward training process, five successive normal ECG beat, recorded before the missing segment, was taken for training which are expressed as FB1, FB2… FB5; and similarly, for backward training, three normal beats, occurred after missing segment, were chosen, mentioned as BB1, BB2…BB5 (the FB1 and BB1 were nearest to the missing segment and FB5 and BB5 were farthest ones).

In forward training, FB5, FB4… FB2 was used for training the network using multiagents, whereas FB1 was kept for validation through RL, that will be discussed later. At first, beat normalization and standardization was performed in order to smooth the training of LSTM-RNN using following equations,

$$\lambda = \sum_i^{\tau} \mathrm{BT}_i \Big/ \tau$$

$$\rho = \sqrt{\sum_i^{\tau} (BT_i - \lambda) \Big/ \tau} \quad (4)$$

where ‘BT_i’ represents i th ($i = 1, 2\ldots \tau$) sample of the signal BT, created by cascading FB5, FB4,..FB2 with combined length ‘τ’; λ and ρ represent the mean and slandered deviation of segment BT. Finally, the standardization was computed using,

$$\mathrm{BT}_i^S = (\mathrm{BT}_i - \lambda)/\rho, \ \ \text{where} i = 1, 2, \ldots\tau \quad (5)$$

In this way, the standardized signal ‘BT^{S}’ was generated that is combination of FB5, FB4… FB2 in forward training process, from which four agents were created using fours features from each beat, as mentioned earlier, i.e., agent-1 consists of cascaded P-waves, from each four beat. In this way, features of each fictitious domain of normal beats were separated and training was done independently for better result. Now, each agent, ‘AG’ with number of sample M, was used to train a LSTM-RNN using the above-mentioned structure by ‘r th’ sample of AG as input layer and ‘$r+1$ th’ sample of AG as output layer, where $r = 1, 2\ldots M$-1. The network parameters are depicted in Table 1. The ‘learning rate’ was chosen using ‘random search’ algorithm, so that the network was trained to its optimal state. The number of epochs were chosen 500, because in some cases, training accuracy drastically decreases to less than 300 epochs. Therefore, for optimal training, this parameter was chosen as 500. The rest of parameters were chosen in such a manner that, the overall root mean squared error (RMSE) was as low as possible along with low convergence time. In this way, the network was so trained that using an input value, it can predict the next upcoming sequence, following the pattern of respective agents, with given sample number.

For backward training process of LSTM-RNN, the BB2, BB3… BB5 was used for creating training agent in a similar manner as mentioned earlier, only except the training sequence. After normalization and standardization process, four separate agents were created, for backward training. Now, the input layer was created by l th sample and output layer was l-1 th sample of each agent, where l = 2, 3,..L and ‘L’ represents the length of each agent. In this way, the backward LSTM-RNN was trained in such a way that it can generate a predicted segment in reverse order of the sequence during its original production.

Table 1
Network parameters used in LSTM-RNN.

Parameters Name	Value
Training function	‘adam’
Learning rate (LR)	0.005
Maximum epochs	500
LR drop factor (in every 100 epochs)	0.2
Number of hidden units	200

The main aim of bidirectional training was to predict the missing segment in such a way that it can best fit within the missing domain without creating any sharp fluctuation at the two ends after cascading. The Bi-LRNN, thus ensured to predict the missing segment aligning to its original baseline. A pictorial representation of training progress of LSTM-RNN is shown in Fig. 3(a).

2.5. Multiagent reinforcement learning (MARL) process

While performing a blind prediction, the network has no idea about the pattern of output sequence within a varying environment. The procedure of blind prediction is explained in following equation,

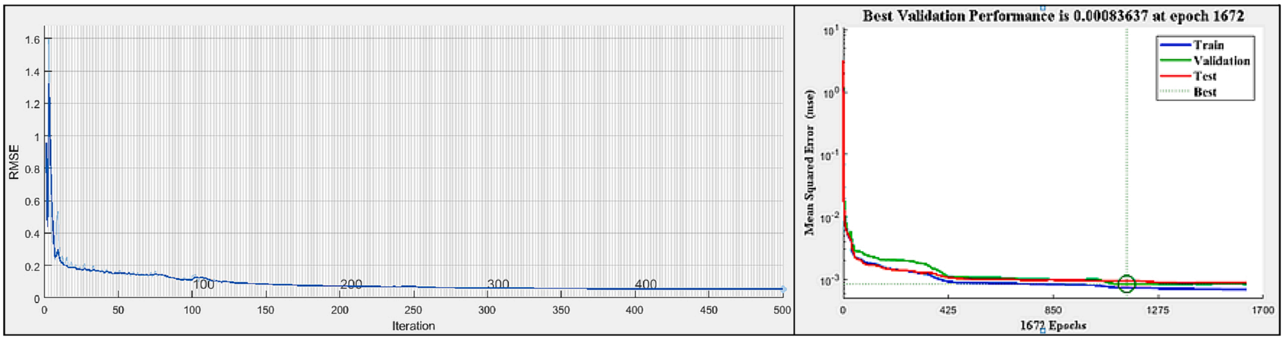
$$X_i \xrightarrow{input} \Theta \xrightarrow{output} Y_i, \text{where}, \begin{cases} i = 1, X_i = \alpha \\ i > 1, X_i = Y_{i-1} \end{cases} \quad (6)$$

where X_i and Y_i represent the input and output layer in i th iteration of trained network’ Θ’. Initiation of prediction was executed by known sample ‘α’, which was the end sample of original signal; and using that sample, the next sample was predicted by the trained network, ‘Θ’. Prediction of further samples was done using the last predicted sample in each iteration; hence the original pattern was not known to the network. To recover this problem, that is to make the output sequence knowledgeable about the varying environment, in this work, multiagent reinforcement learning (MARL) is proposed.

In MARL system [26], each agent learns using an ‘environment’ to enrich an ‘agent goal’ utilizing a learning architecture [20]. The environment is capable of making the agent knowledgeable using ‘actuator’, through which the learning agent acts on its environment. The learning agent has four different elements viz. 1) *learning element*, which learns and updates its own weights, as per the ‘reward’, provided by *critic*, 2) the *critic element*, hence compares the *learning element* response to the environment output and reacts with the *learning element* through ‘sensor’, 3) *performance element* that generates necessary decisions to make further improvement based on each agent inputs, and finally 4) *performance generator* provides the redolent actions that are necessary for newsy and instructive events.

In this proposed method, as the network has no idea about the upcoming pattern of missing segment, reinforcement learning was implemented to improve its output behavior. As shown in Fig. 1 the *learning element* is the trained LSTM-RNN, which is capable of predicting upcoming sequence by providing the last predicting sample as input layer. Now, this upcoming predicted sample was approaching to the original sample, a ‘reward’ signal was generated as (Y_i-X_i), where Y_i is the predicted value by LSTM-RNN using Y_{i-1} sample, and X_i is the original value of i-th sample in FB1 for forward training process (in BB1 for backward training). This ‘reward’ signal represents the deflection of predicted data from original data which should be corrected in each sample prediction. This ‘reward’ or the prediction error was used to train the *critic* element, which is a multilayer perceptron neural network (MLPNN). The input layer of this NN was created by predicted sample in each iteration of RNN, i.e., Y_i and the output layer was created by respective prediction error. The final training of this network was done after the prediction of entire BT signal, with 2000 epochs and learning rate of 0.8, in gradient decent back propagation algorithm. This *critic* network was trained, so that while predicting the final missing segment, it could provide necessary corrections to Bi-LRNN output to perform more accurate prediction.

Thus, after creating each agent, validation of LSTM-RNN was performed by RL using respective segments of FB1 for forward training (BB1 For backward training). The training process started by predicting each missing sample and the error between that predicted sample and original sample was used to update the weights of RNN using the following agent function;



(a) (b)

Fig. 3. (a) Training progress of LSTM-RNN using 500 epochs. (b) Training performance of critic network.

$$\omega_t = \omega_{t-1} + \eta \times \left[tanh\left(\partial Y_{t-1} / \partial X_{t-1} \right) \right] + b \tag{7}$$

where ω_t is the weight of Bi-LRNN at time instant t of RL, $(\partial Y/\partial X)$ is the improvement factor updated by hyperbolic tangent operator; η=random number between [0,1] and b is bias value.

In this way, in each iteration of RL, each successive sample was predicted with updating the weights using above mentioned equation, and the error value was stored for training the *critic* network which was further used during final prediction.

The final prediction of missing segment was carried out using Bi-LRNN with updated weightages and the *critic* network. The *critic* network was designed with 4 hidden layers with 'logsigmoidal' training function with 0.02 learning rate and 2000 epochs. The training performance of this network is shown in Fig. 3(b). After prediction of each sample using Bi-LRNN, that output value was fed into *critic* and the network output or *reward* was further added to Bi-LRNN output, which was considered as the final predicted value of missing sample. In this way, each four agents were used to predict each four segments independently. Now to generate the combined structure of each predicted segment, a 'coordinator agent' was proposed, as mentioned below.

Coordinator Agent: The initial task of 'coordinator agent' was to predict the number of missing beat/segments, followed by the allocation of length for each segment (for an entire beat, length of each agent), using extrapolation algorithm. At first, the number of complete missing beat 'N_{beat}' was predicted by following equation,

$$N_{beat} = roundoff\left[\left(N_{miss} / HR \right) - 0.34 \right] \tag{8}$$

where N_{miss} represents the number of missing samples and HR represents the average heart rate computed from training beats. Now, the coordinator agent has two different functions, 1) to predict the number of samples in each agent that would be cascaded, and 2) to predict the number of samples in incomplete beat with length $\{N_{missing} - (HR \times N_{beat})\}$. To perform this operation, a feed forward back propagation neural network was used in this agent, with input layer containing beat length and four output layers containing length of four agents that were used during training of Bi-LRNN from training beats. This network was trained using 'log-sigmoidal' training function with 2000 epochs, 2 hidden layers with 30 neuron each and learning rate 0.05. Now, after completion of training of this network, the 'coordinator agent' further predicted the number of sample that should be provided to each predicted agent using N_{beat} as input layer. To perform the second task, extrapolation algorithm was implemented to predict the number of missing samples in each agent to best fit the missing segment. In addition, to match the baseline at the two ends of missing segment, the following equation was used,

$$S_{lp}1 = (Y_N - Y_1) / N_{mis}$$

$$S_{lp}2 = (\xi_1 - \xi_2) / (N_{mis} + 2)$$

$$Y'_i = Y_i - \left[\{ Y_1 + (i \times S_{lp}1) \} + \{ \xi_2 + (i \times S_{lp}2) \} \right] \tag{9}$$

where Y_i' and Y_i represents the i^{th} $(i = 1, 2 \ldots N_{miss})$ sample of predicted and final baseline-aligned signal; ξ_2 and ξ_1 represents the end samples of original signal, occurred before and after the missing segment.

In this way after allocation of sample length to each predicted segment (i.e., each agent response), the 'coordinator agent', finally cascaded all segments sequentially with aligned baseline, so that the continuation of entire predicted segment did not hamper.

3. Results

The proposed algorithm was tested on MIMIC-II database, available on Physionet [17]. The BIDMC or MIMIC-II records contain various physiological signals mentioned earlier, among which the single lead ECG records, were used for testing. The entire algorithm was performed in MATLAB platform. Now, the performance of beat delineation and quality of predicted signal, were measured using various evaluation parameters, mentioned below.

3.1. Performance metrics

The feature extraction and training process was initiated by R-peak detection and beat delineation. The performance of peak detection was measured using the following parameters,

$$S_E = \frac{TP}{TP + FN}$$

$$+P = \frac{TP}{TP + FP} \tag{10}$$

where True Positive (TP): number of perfectly detected peak, False negative (FN): number of peak undetected and False positive (FP): number of wrong detected peak. To compare the accuracy of prediction of the obtained result, with the previously published works, three parameters were analyzed as,

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (P_i - Q_i)^2}$$

$$Q_1 = \left(1 - \frac{(RMSE)^2}{\sigma} \right)$$

$$Q_2 = (CORR) \tag{11}$$

where P_i and R_i represents the i th sample of reference and predicted signal P and Q, respectively with length N ; σ represents the variance of reference signal; and CORR represents the correlation coefficients between R and P signal. To measure the distortion error of various beat features viz. RR intervals, R, P, Q-peak amplitude, another quality index called 'fractional distortion error' (FDE) was also measured as,

$$FDE = \frac{1}{n}\sum_{i=1}^{n}\left(\left|\frac{f_R - f_P}{f_R}\right|\right) \tag{12}$$

where f_R, and f_P represent measured value of corresponding feature in reference and predicted signal; n is the number of detected features.

3.2. R-peak detection performance and segmentation

The prediction algorithm was initiated by R-peak detection using derivative based approach, followed by the segment classification using discrete wavelet transform. The average slope energy of QRS complex is higher than the other segments within a beat; hence, sample to sample differentiation is a beneficent mathematical approach to detect the R-peaks. The average S_E and + P was obtained as 99.96 and 99.92 for MIMIC-II records. After detecting each R-peak, beat delineation was done using DWT. Generally, the P, T-wave occur below 10 Hz frequency range, therefore using DWT, each ECG beat was decomposed up to a frequency subband mentioned above, and using those subbands, P-wave and T-wave and all onset and offset values were computed using sample to sample calculation with minimum slope amplitude. Fig. 4 shows the pictorial representation of beat delineation along with wavelet transformed signal.

3.3. Performance on missing data prediction

The prediction performance was tested using RMSE and other parameters viz. Q_1 and Q_2 [27] which is depicted in Table 2. The performance result is separately shown for both forecasting and prediction, using only Bi-LRNN and the proposed Bi-LRNN + RL system, respectively. The forecasting was computed to analyze the accuracy of prediction of the trained neural network, by providing the reference signal as an input layer. During prediction, the network (both Bi-LRNN and MARL) blindly predicted the upcoming sequence using past predicted sample. It is clear from the Table that both prediction and forecasting performance were improved using the proposed algorithm. The FDE of various features are shown in the same Table 2. The FDE is a measure of distortion of original feature in forecasted and predicted signals both; hence, a low value of this parameter represents less distortion i.e. more perfect prediction. The improvement of accuracy of various beat features shown in this Table satisfies this fact that using the proposed approach of prediction, important clinical features were almost restored. It was also observed that, with the increment of number of beat

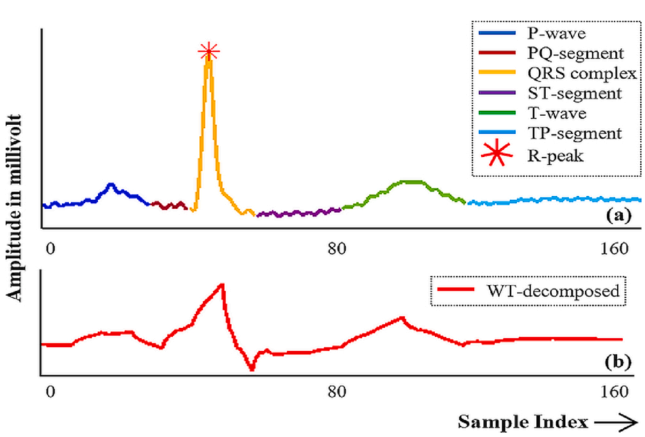


Fig. 4. ECG beat classification (a) various fictitious domain of single ECG beat with detected R-peak; (b) wavelet decomposed signal of original beat.

Table 2
Experimental Result on Various ECG Records.

Tool	Signal	Q_1	Q_2	FDE			
				P-pk[a]	Q-pk	R-pk	RR[b]
Bi-LRNN	Fore	0.961	0.981	0.018	0.016	0.02	0.01
	Pred	0.889	0.921	0.028	0.032	0.027	0.02
BiLRNN + RL	Fore	0.992	0.996	0.011	0.017	0.011	0.007
	Pred	0.915	0.962	0.014	0.027	0.018	0.01

[a] pk: peak amplitude.
[b] RR: RR interval.

prediction, RMSE increased along with decrement of Q_1 and Q_2. Fig. 5 shows the variation of RMSE, Q_1 and Q_2 with respect to predicted beats. An average value of these parameters was obtained in this proposed work was 0.915 and 0.961 for 44 MIMIC-II ECG records, respectively. A pictorial representation of prediction is shown in Fig. 6. The original signal is shown in Fig. 6(a) with the missing segment shown in 'dotted-red' color. Fig. 6(b) and (d) shows the predicated and forecasted segment using the trained Bi-LRNN, with average RMSE of 0.0432 and 0.1352 respectively. It is clear from these Figures that using the known input sequence, the network can forecast the upcoming sequence with very low RMSE, but the performance of blind prediction is weak. Therefore, in this proposed work, multi agent reinforcement learning was used to further update the Bi-LRNN and create a *critic* network, to improve the performance of blind prediction which is shown in Fig. 6(e) with RMSE 0.0411. Fig. 6(c) shows the forecasted signals with the proposed prediction algorithm with RMSE 0.0287. It is clear form this analysis that, using reinforcement learning, both of the prediction and forecasting accuracy was increased.

4. Discussion

Table 3 shows a comparative study on prediction with recently published works on ECG signal. In [5], authors proposed an infinite impulse response function for prediction along with a particle swarm optimization for optimizing the filter coefficients. J. McBride et al. [7] introduced various improved algorithms that provided satisfactory result on prediction. As compared to these works, the proposed method uses bidirectional LSTM-RNN for blind data prediction, and after each sample estimation, the reinforcement learning system provided a reward or error response, which was used for further correction to provide optimal predicted value.

Missing data prediction [2] and corrupted data estimation [3] of ECG was also performed using linear prediction and feature extraction from clean ECG beats using PCA which were further classified to predict the missing segment [4]. With an improved computational technique, pattern recognition-based prediction [6], reduced the prediction error between the predicted and reference signal. X. Dong et al. [8] proposed a

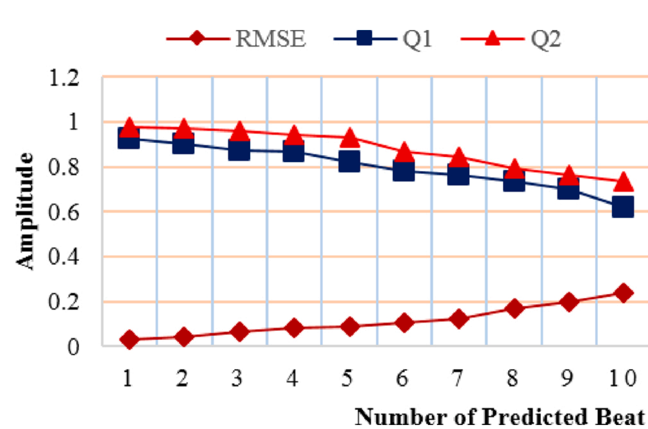


Fig. 5. Variation of RMSE, Q_1, and Q_2 with the number of predicted beats.

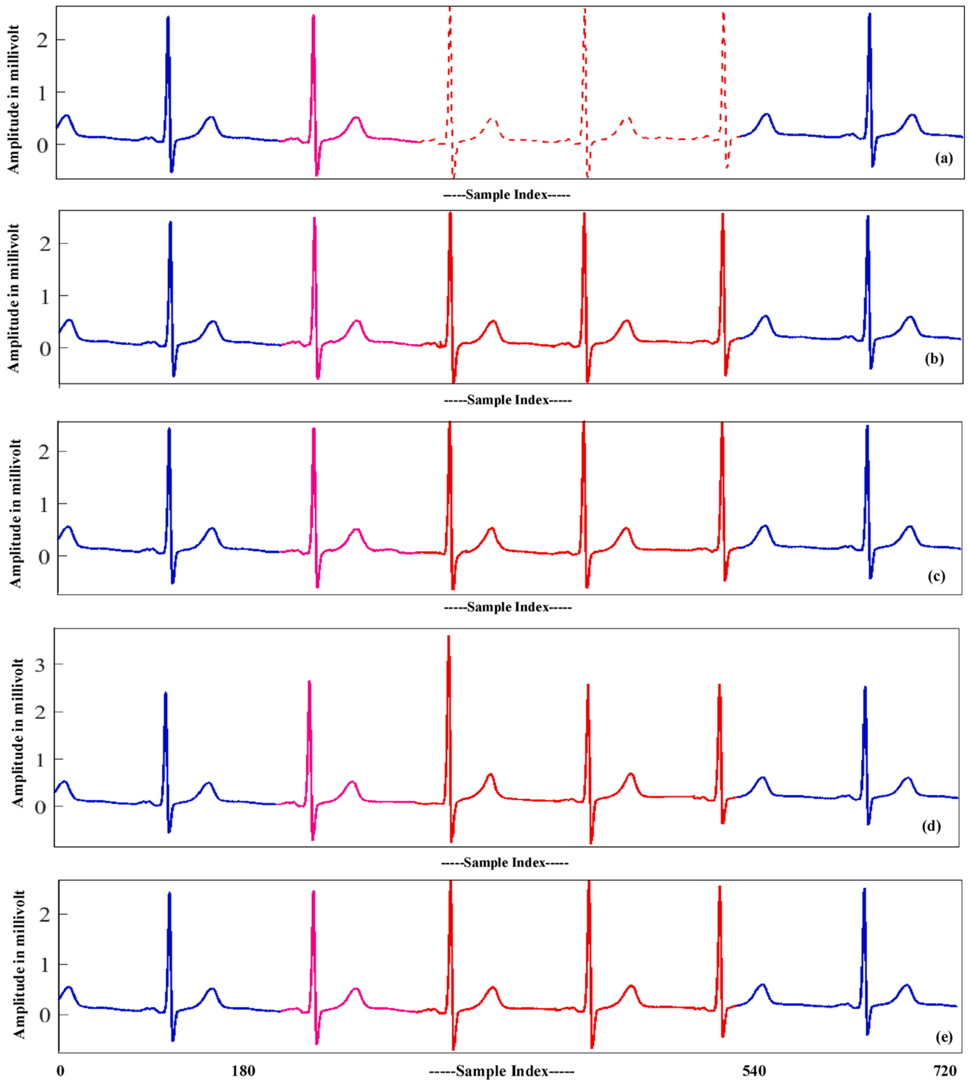


Fig. 6. Experimental result of reference signal marked in 'blue' color with validation data marked in 'pink' and missing segment marked in 'red- dotted' line; forecasted segment using reference signal, marked in 'red-solid' line using only LSTM RNN (b) and proposed method (c); blindly predicted segment marked in red-solid line using only LSTM RNN (d) and proposed method (e).

Table 3
Comparative Study with Existing Methods Tested on MIMIC-II ECG records.

Related works	Tool	Q_1	Q_2	No. of records
A. Hartmann [5]	IIR filter coefficient with PSO	0.884	0.933	44
	Straightforward simulation	0.910	0.945	
J. McBride [7]	Iterative retraining	0.925	0.954	44
	Accumulated Averaging	0.934	0.958	
Proposed	**Bi-LRNN + RL**	**0.915**	**0.961**	**44**

new entropy encoding based missing data estimation, which provided low percentage error with respect to various previously proposed methods e.g., linear interpolation, bootstrapping. To improve predictor distribution more flexible, in [9], authors proposed Bayesian approach for missing data prediction implemented on ECG records of non-ICU patients. In [11], LSTM-RNN was utilized for missing data estimation with improved accuracy.

As compared to these published works, in this work, the bidirectional LSTM-RNN was proposed using forward and backward training process, so that the predicted signal can best fit within the missing segment. During long term ECG monitoring, sudden loss of intermediate segment is a common factor caused by various issues like probe loosening, body movement etc. In addition, for telemonitoring applications, mislaid of data may take place due to transmission line failure. To predict those missing segments, in this work, deep neural network was utilized. To improve prediction accuracy, reinforcement learning was introduced to provide necessary corrections to predicted sample in each iteration. The multiagent architecture independently classified the beat features and predicted each segment in 'cooperative learning' using a 'coordinator agent' which successfully restored the clinical features within predicted segment. The bidirectional architechture of prediction was computed in such cases, where sufficient training dataset were available for forward and backword tarining process, otherwise unidirectional LSTM-RNN was implemented (i.e. forward and backword tarining, if missing of segemnt occured at the end and beginning of original signal, respectivley). The alogrithm was initiated by accuarte R-peak detection, failing which beat classification procedure would fail resulting in inaccuatre prediction. The computation time is little bit higher than the previously publishd works, and it increased with the increment of length of missing segment. The proposed algorithm can be applicable in real-time telemonitoring applications to previse/predict the missing segment so that various features like heart rate variablity etc. might not hamper.

Table 4 describes a head-to-head comparison of derived result, with

Table 4
Comparison of derived ECG features.

Related works	Database	SF	RMSE	RR (ms)	
				Original	Predicted
N. Theera-Umpon, 2008 [2]	MITBIH-NSR[a]	128	–	0.733	0.886
H. Verma, 2019 [11] ma	MITDB	360	0.01–0.10	–	–
Proposed	**MIMIC-II**	**125**	**0.087**	**0.664**	**0.608**

[a] NSR: Normal Sinus Rhythm.

the previously published works, mentioning the database used along with the sampling frequency (SF). The 'RR (ms)' represents the average RR-interval (converted to millisecond) of original and predicted signal. The improvement of this parameter ensured better performance of the proposed work. The RMSE in the proposed algorithm, measured for single beat prediction, was less than 0.01 (refers to Fig. 5) and it increased with the increment of number of predicted beats. Therefore, the average RMSE obtained after 5 consecutive beat prediction, is mentioned in Table 4 for comparison.

5. Conclusion

This article presented missing data prediction theory of ECG signal using bidirectional LSTM recurrent neural network and multiagent reinforcement learning system. Four agents were selected which basically represented four time-domain features of ECG beat. The agent learns independently; and finally, predicted the entire missing segment using cooperative learning. After implementing on 44 MIMIC-II records, very low RMSE was obtained between the predicted and reference signal with correlation factor higher than 0.9. It is worthwhile to mention here that the prediction of missing data from any single channel ECG signal using past and future clean ECG beats from the same lead i.e., the prediction theory was completely independent of lead category viz. chest, precordial and limb lead. The prediction process was initiated by R-peak detection and beat delineation; therefore, for any single channel ECG signal, after detecting the R-peaks, the preceding steps of prediction can be applicable. As this work introduces Bi-LRNN and RL process, the training and prediction process consumed comparatively higher time for computation. Selection of various network parameters, used in this work, was based on observation, and they were so chosen that convergence time be lower along with higher training accuracy. The entire work can be broadly classified into three stages viz. LSTM-RNN training, multiagent RL training and final prediction using LSTM-RNN and RL. The average computation time of initial two training processes were 0.205 and 0.0102 s/sample, with 500 and 2000 epochs, respectively (these processes were performed once for prediction, irrespective of missing segment length). The average execution time of final prediction process was 8.8 millisecond/sample computation. The prediction performance can be further enhanced using increased number of training dataset for both Bi-LRNN and RL system, with increased cost of computation time.

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CRediT authorship contribution statement

Soumyendu Banerjee: Writing - original draft, Data curation, Methodology, Software, Validation. **Girish Kumar Singh:** Conceptualization, Visualization, Investigation, Supervision, Writing - review & editing.

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Declaration of Competing Interest

The authors report no declarations of interest.

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