Abstract—This paper aims at developing a system identification based model for the generation of electrocardiogram (ECG) cycles using the combination of arterial blood pressure (ABP) and central venous pressure (CVP) signals acquired from the same subjects at the same time. The method employs a system identification based approach using Prediction Error Minimization (PEM) technique to develop a patient specific cardiovascular model. The input (ABP and CVP) and output (ECG lead II) signals required for model estimation are acquired from MGH/MF waveform database. The input and output signals are preprocessed in the same manner prior to model estimation. At first, the model is developed using the initial first cycle of ABP, CVP signal of a subject as input and simultaneously acquired ECG lead II signal of same subject as output then other cycles of ABP, CVP signals are given as input for validation of the model. Generated ECG cycles are compared with the corresponding ECG cycles available on the database and the accuracy of generated ECG cycles is explicated in terms of best fit percentage.

Index Terms—ABP signal, CVP signal, ECG signal, System Identification.

I. INTRODUCTION

Biomedical signals have been used to illustrate the physiological processes underlying the heart. These biomedical signals may be electrical in the form of potential or current and physical in the form of pressure or temperature. If a system is well known, it is possible to assess the system dynamics by studying the corresponding signals. Most commonly used signal for assessing the activity of heart is ECG signal. This signal comprises of repetitive sequence of P, QRS and T waves, each representing a particular event of heart activity. P-wave results from a trial depolarization, QRS results from ventricular depolarization and T-wave is associated with ventricular repolarisation. Other than ECG signal, other biomedical signals such as ABP, CVP, PAP (Pulmonary Artery Pressure) signals are also used to study heart activity.

Arterial blood pressure waveform comprises of systolic peak, diastolic onset, dicrotic notch and dicrotic peak. Systolic peak follows ECG R-wave and results due to ejection of blood from left ventricle to aorta. Dicrotic notch is a transitional episode resulting due to decline of systolic pressure which indicates closure of aortic valve. Further decrease in systolic pressure continues till it reaches its lowest point (diastolic onset) at end diastole that follows ECG T-wave. Dicrotic peak is the reflected impulse arising due to closing of aortic valve.

CVP waveform is evident in the form of three upward (‘a’, ‘c’ and ‘v’) waves and two downward (x,y) waves. ‘a’ wave appears due to rise in right a trial pressure during a trial contraction, ‘c’ wave is the result of closing of AV valve but not always present. ‘v’ wave indicates the increase in a trial pressure that occurs as a result of a trial filling during ventricular contraction. The appearance of ‘y’ descent is due to rapid decrease in pressure due to blood flowing from right atrium to right ventricle. ‘y’ descent corresponds to onset of P wave in ECG and ‘a’ ascent of CVP signal corresponds to offset of ‘P’ wave in ECG. ‘c’ wave in CVP signal is related to end of QRS segment in ECG. ‘x’ descent and ‘v’ ascent in CVP signal correspond to onset and offset of T wave in ECG. R peak in ECG is located between ‘a’ and ‘c’ waves in CVP tracing [1]. Figure 1 shows the relation among the features of CVP, ABP and ECG signals from the subject of mgh007 record of MGH/MF waveform database.

The mathematical models of heart have proved useful in the better understanding of physiological measures [2]. These models are used for the analysis, simulation, and prediction, detection of abnormalities, training and validation of developed algorithms. A model is used to replicate a system in order to give best possible results in the same way as the original system [3]. A patient specific system of heart may comprise of comparison of past and recent ECGs of an individual [4]. Thus a patient specific model of heart can give an idea of future medical conditions of an individual that cannot be revealed by a sample test. For the diagnosis of unwanted medical conditions of an individual, physiological variables received from non-invasive biomedical sensors can be compared with real time modeled variables [5]. The models can generate practical ECG signals of known characteristics. The statistics used in generating the characteristics of ECG may assist in the performance evaluation of a given technique [6]. The process of numerical ECG simulation is difficult to be described by
mathematical equations. However, diagnosis by component ECG waveform can be described in linguistic terms from medical knowledge [7, 8]. Computers are useful for implementing this kind of qualitative ECG simulation [9]. An implicit database of normal and pathological conditions may be created using these simulated ECGs. This database can be used to test and train medical devices and also it may be useful to train the physicians in better understanding of cardiac conditions [10].

System identification technology has been a popular method for the analysis of the dynamic behavior of biomedical systems. It is a method of building mathematical models of dynamic system based on measured data [11] and is achieved by adjusting the parameters of a developed model until the model output best matches with the measured output. The parameters of the system identification models serve as tools to describe the overall behavior to the system and these are easier to construct as compared to mathematical models. As compared to mathematical models, system identification based models are less common and comprise of very small physical insight. Physiologic mechanisms can be characterized using the measured input-output data of a system. The study involves conversion of measured data to the mathematical representation of a system including analysis and transformation of developed model. This method can also be used for the prediction of future output by means of the developed model.

![Figure 1. Features of CVP (top), ABP (center) and ECG II (bottom) signals from mgh007 record with their relation to one another](image)

ON- Onset, PK-Peak, DN-Dicrotic Notch, DP-Dicrotic Peak

Concept of modeling of biomedical signals has been proposed by many researchers. The research in the area includes system identification based model for short term analysis of beat to beat fluctuations in heart rate signals obtained from ECG, non invasive blood pressure and instantaneous lung volume [12],[13],[14] and another model for theoretical validation of the same [15]. Further, a model for the generation of RR-tachograms [16], a dynamical model based on data driven approach to impersonate real ECG signal [17] and use of this model for generation of ECG, BP and respiration signals are also suggested [18]. Artificial models for generating multi-lead ECGs using 3D vector cardiomogram formulations [19], hidden Markov model (HMM) for changing over between normal and abnormal beats [20], a Gaussian wave-based state space model to track the ECG characteristic waveforms using an extended Kalman filter [21] are also suggested. Other contributions to the field of modeling of physiological signals include mathematical modeling of electrical activity of heart [22], simulation of qualitative ECG using fuzzy sets [9], a model for simulating Bundle Branch and Fascicular Block [23], numerical simulation of ECG based on partial differential equations [10], modeling the electrical activity of the human heart using Artificial Neural Network [5] and microcontroller based ABP and ECG simulator [24]. Use of wavelets for complicated signal modeling [25] and orthonormal wavelet basis functions for efficient characterization of signal [26, 27, 28] are also found in literature. Further, use of Hermite basis function possessing the resemblance to ECG signals for shape determination of one dimensional signal such as ECG [29], clustering of QRS complexes in ECG [30], characterization of QRS complexes based on Hermite coefficients and fuzzy-neural network [31] and joint dynamical model based on state-space using Bayesian estimation procedures such as the Kalman filter (KF) to provide synchronized estimations of CV signals, including the ECG, ABP, photoplethysmograph (PPG), central venous pressure (CVP), and pulmonary artery pressure (PAP) [32] are also proposed in literature.

It is seen from literature that various models of the electrical activity of heart have been developed. These include system identification based approach [12]-[14] mathematical modeling [22], Artificial Neural Network [5], data driven approach [17]. Wavelet and Hermite decomposition approach have also proved useful for shape
determination and characterization of ECG [29]. Whereas, an ECG model based on measured physiological data is not reported in literature. Synthesis of ECG from measured ABP and CVP signal has been shown to be a potential modeling approach in this paper. We present a system identification based approach for modeling of ECG that is inspired with adequate correspondence of features of ABP, CVP to ECG signal. The inputs to our model are simultaneously acquired ABP and CVP signals and output is ECG lead II signal that mimics ECG lead II signal acquired from the subject at the same time.

II. MATERIALS

A. State Space Model

State space models are used in control engineering to describe the complex systems which are of higher order and consist of several parameters as input and output and a large number of measurements. State space structure is the powerful way to represent a system. The state-space representation is the most reliable Linear Time Invariant (LTI) model to use for computer analysis.

In a linear time invariant sense, a discrete time state space model appears as the first order finite difference model [33] –

\[
\begin{align*}
\dot{x}(t) &= Ax(t) + Bu(t) \\
y(t) &= Cx(t) + Du(t)
\end{align*}
\]

The system of first-order differential equations (equation 1) is known as the state equation of the system and (equation 2) is called output equation. Here, \( u(t) \) denotes input vector or control vector, \( y(t) \) and \( x(t) \) are output vector and state vector respectively. Matrices \( A, B, C, D \) are state matrix, input matrix, output matrix and matrix \( D \) is feed through or feed forward matrix. \( D \) is often selected as zero matrix for the purpose of simplicity.

The discrete state-space model is given by-

\[
\begin{align*}
x(kT + T) &= Ax(kT) + Bu(kT) \\
y(kT) &= Cx(kT) + Du(kT)
\end{align*}
\]

Where, \( K \) is the sampling instant and \( T \) is the sampling interval.

Replacing \( x(kT) \) by \( x(k) \) above equations (3) and (4) reduce to,

\[
\begin{align*}
x(k+1) &= Ax(k) + Bu(k) \\
y(k) &= Cx(k) + Du(k)
\end{align*}
\]

This equation can also be written as –

\[
\begin{bmatrix}
x_1(k + 1) \\
x_2(k + 1) \\
\vdots \\
x_{n-1}(k + 1) \\
x_n(k + 1)
\end{bmatrix} =
\begin{bmatrix}
0 & 0 & \cdots & 0 & 0 \\
0 & 0 & \cdots & 0 & 0 \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
0 & 0 & \cdots & 0 & 1 \\
-a_n & -a_{n-1} & \cdots & -a_2 & -a_1
\end{bmatrix}
\begin{bmatrix}
x_1(k) \\
x_2(k) \\
\vdots \\
x_{n-1}(k) \\
x_n(k)
\end{bmatrix} +
\begin{bmatrix}
0 \\
0 \\
\vdots \\
0 \\
b
\end{bmatrix}
\]

\[
y(k) =
\begin{bmatrix}
1 & 0 & \cdots & 0
\end{bmatrix}
\begin{bmatrix}
x_1(k) \\
x_2(k) \\
\vdots \\
x_{n-1}(k) \\
x_n(k)
\end{bmatrix}
\]

\[
A =
\begin{bmatrix}
0 & 0 & \cdots & 0 & 0 \\
0 & 0 & \cdots & 0 & 0 \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
0 & 0 & \cdots & 0 & 1 \\
a_n & a_{n-1} & \cdots & a_2 & a_1
\end{bmatrix}, \quad B =
\begin{bmatrix}
0 \\
0 \\
\vdots \\
0 \\
b
\end{bmatrix}
\quad \text{and } C =
\begin{bmatrix}
1 & 0 & \cdots & 0
\end{bmatrix}
\]

Where, \( x(k) = \begin{bmatrix}
x_1(k) \\
x_2(k) \\
\vdots \\
x_{n-1}(k) \\
x_n(k)
\end{bmatrix} \)
Where,

Here, \(u(k)\) and \(y(k)\) represent the system input and output at \(k^{th}\) sampling instant.

The transfer function of a LTI system in continuous time is given by –

\[ y(t) = H u(t) \]  

(9)

The transfer function \(H\) in Laplace domain in terms of state matrices is given by –

\[ \hat{H}(s) = C(sI - A)^{-1}B + D \]  

(10)

Where, \(I\) is the identity matrix, this equation can also be written as –

\[ \hat{H}(s) = \frac{b_0s^n + b_1s^{n-1} + \cdots + b_m}{s^n + a_1s^{n-1} + \cdots + a_n} \]  

(11)

And \(Z\) transform of this system is given by –

\[ \hat{H}(Z) = \frac{b_0Z^n + b_1Z^{n-1} + \cdots + b_m}{Z^n + a_1Z^{n-1} + \cdots + a_n} \]  

(12)

B. Prediction Error Minimization Method

Parameter estimation in dynamic systems is regarded as subpart of system identification to develop dynamic models from the measured data. Estimation of parameters is a very important task in modeling the different type of processes. Prediction Error Methods can be applied to reasonably random model parameterizations. This method considers the accuracy of the predictions computed for the observations, rather than the model mismatch. These methods bear resemblance with maximum likelihood methods and used for the parameter estimation of dynamical models and time series data [34]. The objective of prediction error minimization (PEM) method is to build a predictor and compare its predictions with available data using some suitable measure [35]. Predictor considers the measurement data in to account which reduce the prediction error to a large extent.

PEM methods do not guarantee long-term prediction accuracy, which is a critical factor for purposes such as analysis, simulation, or model-based control design [36].

Let the signal-generating system represents the colored-noise perturbation as a filtered white-noise sequence. Thus the input–output data to be used for identification are assumed to be generated in the following way [37]

\[ y(k) = G(q)u(k) + H(q)e(k) \]  

(13)

Where \(e(k)\) is a zero-mean white-noise sequence that is statistically independent from \(u(k)\), and \(G(q)\) represents the deterministic part and \(H(q)\) the stochastic part of the system.

If we denote this innovation model by means of transfer functions, then, in analogy with the signal-generating system (equation 13), we get the following parameterizations of the deterministic and stochastic part:

\[ G(q, \theta) = D(\theta) + C(\theta)(qI - A(\theta))^{-1}B(\theta) \]  

(14)

\[ H(q, \theta) = I + C(\theta)(qI - A(\theta))^{-1}K(\theta) \]  

(15)

Note that the matrix \(A\) appears both in \(G(q)\) and in \(H(q)\). Therefore it characterizes the dynamics of both the deterministic and stochastic part of system mentioned in equation (13).

The prediction error for system mentioned in equation (13) is given by the following relation –

\[ e(k) = H^{-1}(q)[y(k) - G(q)u(k)] \]  

(16)

These errors are for given data \(u\) and \(y\) as the functions of \(G\) and \(H\). These in turn are parametrized by the entries in state space matrices defined in equation. The most common parametric method is to determine \(G\) and \(H\) by minimizing

\[ V_N(G, H) = \sum_{t=1}^{N} e^2(t) \]  

(17)

The PEM method tries to minimize the error by search of suitable parameters. If model structure is different for the process, the parameter is determined in such a way that prediction error is minimized under its structure limitations.

C. MGH/MF waveform Database

MGH/MF waveform database is the collection of electronic recordings of hemodynamic and electrocardiographic waveforms of patients in critical care units. This database signifies a wide spectrum of physiologic and path physiologic states. The typical recordings include signals from three ECG leads, arterial pressure, pulmonary
arterial pressure, central venous pressure, respiratory impedance, and airway CO2. Some recordings include intra-cranial, left atrial, ventricular and/or intra-aortic-balloon pressure waveforms. The sampling rate for the signals of this database is 360 samples/second. ABP, CVP and ECG lead II signals of four records are taken for the analysis.

III. SYSTEM IDENTIFICATION BASED INPUT OUTPUT MODEL

The method employs the use of hemodynamic (ABP and CVP) and electrocardiographic (ECG lead II) recordings available in MGH/MF waveform database. This requires ABP, CVP and corresponding ECG lead II signals to be separated from other signals such as ECG lead I and lead V, pulmonary artery pressure (PAP), CO2 and respiratory signals available in the records of above mentioned database. At first, ABP and CVP signals are managed in suitable format as input signals and corresponding ECG lead II signal as output signal in the estimation dataset. Each input and output signals in estimation dataset have same number of samples. The samples are selected such that number of samples in ABP and CVP represent a complete ECG cycle. For this purpose the knowledge of relation between ABP and CVP to ECG signals as discussed in section I is taken into account. The flow chart of system identification based modeling of ECG using prediction error minimization approach is given in Figure 2. This input-output dataset is first preprocessed by symmetric wavelet (sym6). Then the difference between the approximation coefficients for each signal in the dataset at level 3 and 8 is taken for further processing by 10 point moving average filter. The resulting input and output dataset are detrended by subtracting the offset values of input and output dataset at equilibrium from the actual input-output dataset. The offset values $\bar{x}$ and $\bar{y}$ of input data ($u$) and output data ($y$), are estimated as the mean of the measured sequences and given by the following relation –

$$\bar{x} = \frac{1}{N} \sum_{k=1}^{N} u(k) \quad (18)$$

$$\bar{y} = \frac{1}{N} \sum_{k=1}^{N} y(k) \quad (19)$$

This process eliminates the linear trend in the data and thus helps to estimate the non-linear system near to the point of linearization in the selected operating range. Secondly, these offset terms may be considered as unknown parameters in the identification process of corresponding model and these are required to be estimated. Both these cases mentioned above are the special cases of signal prefiltering.

Initially a higher (6th) order state space model is obtained for record mgh003. This estimated higher order model possesses most of the information in the data. Then most significant states of this model are extracted in model order reduction step. Two methods of model order reduction process are known. In first method, model order reduction step employs visual examination of poles and zeros in pole zero plot. This process includes neglecting the overlapping poles and zeros and selection of non-overlapping poles and zeros as a part of actual system dynamics. Another method of model order reduction is employed by eliminating the diagonal entries of joint grammians that are weakly coupled to output. We have used examination of state space realization of balanced grammians method for model order reduction.

IV. RESULTS AND VALIDATION

The modeling approach is applied on the four records of MGH/MF waveform database. For modeling the record mgh003, the following type of 4th order state space model is obtained after model order reduction –

$$\begin{bmatrix}
x_1(k+1) \\
x_2(k+1) \\
x_3(k+1) \\
x_4(k+1)
\end{bmatrix} =
\begin{bmatrix}
0.96607 & -0.23143 & -0.026671 & -0.00043566 \\
0.06034 & 0.7459 & 0.20026 & -0.07503 \\
0.10244 & 0.097181 & 0.73791 & 0.15161 \\
-0.22039 & 0.046451 & -0.13043 & 0.83639
\end{bmatrix}
\begin{bmatrix}
x_1(k) \\
x_2(k) \\
x_3(k) \\
x_4(k)
\end{bmatrix} +
\begin{bmatrix}
-1.7809 & -0.35109 \\
-4.3395 & 0.55339 \\
3.9565 & -1.6319 \\
0.72006 & 1.7817
\end{bmatrix}
\begin{bmatrix}
u_1 \\
u_2
\end{bmatrix} \quad (20)$$

$$y(k+1) =
\begin{bmatrix}
1.6766 & -0.12002 & -0.063134 & 0.008763
\end{bmatrix}
\begin{bmatrix}
x_1(k) \\
x_2(k) \\
x_3(k) \\
x_4(k)
\end{bmatrix} \quad (21)$$
Where, $x$, $u$, $y$ have the same meaning as defined in equation (5), (6), (7) and (8). Loss function ($V$) is $4.052 \times 10^{-6}$ and Prediction Error ($PE$) is $5.16979 \times 10^{-6}$.

Loss function ($V$) is calculated from prediction error ($PE$) by using the following formula:

$$V = PE \left[ \frac{1 - \frac{d}{N}}{1 + \frac{d}{N}} \right]$$

(22)

Where, $PE$ denotes the prediction error. '$d$' Represents the number of estimated parameters and '$N$' is the number of values in the estimated dataset. $PE$ is the measure of model quality by simulating the situation when model is simulated on different dataset. The value of $PE$ and loss function is minimum for most accurate model.

---

**Fig 2. Flow chart of system identification based modeling of ECG**
**Fig 3.** Generated ECG cycles for record (a) mgh003, (b) mgh004, (c) mgh005 and (d) mgh007 compared with actual ECG cycles

**Table I.** Results of System Identification Based Modeling of ECG

<table>
<thead>
<tr>
<th>Record No.</th>
<th>Age/ Sex</th>
<th>Estimation Data</th>
<th>Transfer Function</th>
<th>Validation Dataset</th>
<th>Beat Type</th>
<th>Best Fit %</th>
<th>Average Fit %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mgh003</td>
<td>47 F</td>
<td>Normal</td>
<td><strong>ABP to ECG</strong></td>
<td>Normal</td>
<td>Normal</td>
<td>61.0302</td>
<td>55.1909</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>$G(z) = \frac{-1.8113(z - 1.034)(z^2 - 2.162z + 1.454)}{(z^2 - 1.797z + 0.8806)(z^2 - 1.657z + 0.8665)}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mgh004</td>
<td>64 F</td>
<td>Normal</td>
<td><strong>CVP to ECG</strong></td>
<td>Normal</td>
<td>Normal</td>
<td>57.2991</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>$G(z) = \frac{-0.31149(z - 1.089)(z^2 - 1.379z + 0.7543)}{(z^2 - 1.851z + 0.9017)(z^2 - 1.711z + 0.8687)}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mgh005</td>
<td>56 M</td>
<td>Normal</td>
<td><strong>ABP to ECG</strong></td>
<td>Normal</td>
<td>Normal</td>
<td>51.7996</td>
<td>50.7174</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>$G(z) = \frac{0.51093(z - 1.006)(z^2 - 2.336z + 1.416)}{(z^2 - 1.871z + 0.8816)(z^2 - 1.48z + 0.8033)}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mgh007</td>
<td>60 F</td>
<td>Normal</td>
<td><strong>CVP to ECG</strong></td>
<td>Normal</td>
<td>Normal</td>
<td>48.2452</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>$G(z) = \frac{-0.55536(z + 1.033)(z^2 - 2.104z + 1.129)}{(z^2 - 1.835z + 0.8753)(z^2 - 1.547z + 0.8327)}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The estimated model is validated with independent dataset comprising of other cycles of ABP and CVP. Validation dataset is also preprocessed in the same manner as test dataset. The transfer functions of estimated model for the records mgh003, 004.005 and mgh007 along with obtained best fit percentage for each generated ECG cycle compared to actual ECG for each record are shown in table I. Table I shows two transfer functions for each record. The first transfer function shows the relation of first input to output i.e. ABP to ECG and second transfer function shows the relation of second input to output i.e. CVP to ECG. Initially, the model is estimated using first normal cycles of ABP and CVP as input and ECG lead II as output. Synthesis of other ECG cycles is based on window based modeling in which a window is defined of the duration used for model estimation, and generated ECG cycle is stored, then this window is moved along X-axis by the defined window size and ABP, CVP data falling in that window are given as input to the model and generated ECG cycle is combined with the previously generated ECG cycle and so on. Using this process ECG signal of desired duration can be generated if corresponding ABP and CVP data are known. The accuracy for the generated ECG cycle is defined in terms of best fit percentage given by the relation –

$$\text{Best Fit} = \left(1 - \frac{\bar{y} - \hat{y}}{\bar{y} - \bar{y}}\right) \times 100$$  \hspace{1cm} (23)$$

Where, \(\bar{y}\) denotes the measured output i.e actual ECG signal data available from the database of the same duration as ABP and CVP signals data taken for validation of the model. \(\hat{y}\) is the estimated model output i.e. generated ECG signal as model output signal. \(\bar{y}\) is the mean of measured output. This formula gives best fit % for each generated ECG cycle. The accuracy of complete generated length of ECG signal is given as an average of the best fit percentages obtained for each ECG cycle. Figure 3 (a-d) shows the comparison of generated ECG cycles as model output with actual ECG cycles in terms of best fit percentage for records mgh003, mgh004, mgh005 and mgh007 respectively. Figure 4 shows the comparison between 59 generated cycles of ECG as model output with actual ECG cycles.

V. CONCLUSION AND DISCUSSION

A system identification based approach for normal ECG generation using the combination of normal ABP and CVP signals is discussed in this paper. As stated earlier, the method requires preprocessing of validation data in similar way as estimation dataset to generate synthetic ECG from lead II. But the method may be extended to generate synthetic ECG from other ECG leads provided the model estimation dataset comprise of particular ECG lead as output along with ABP and CVP data as input. This approach of ECG modeling may be applied in intensive care units where ECG signals are monitored along with hemodynamic signals such as ABP and CVP signals and thus may enable monitoring of ECG without the positioning of leads for ECG acquisition. There may be a case when patient suffers from severe injury and surgical dressing of patient does not permit to position ECG acquisition leads at the desired places. This approach of modeling ECG may also be regarded as soft sensor acquisition of ECG. The generated transfer functions mentioned in table I may also be used to study stability and step response for different patients in normal/abnormal conditions and state of heart may be explored.
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AUTHOR BIOGRAPHY

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