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Application of Stochastic Process in Signal Processing

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Abstract
In this paper introduction about birth and death Poisson process basic result of the markovian application in queuing theory used in signal processing, signal transfer from some to passion based on the intermediate node, each intermediate node are transformed from signal strength S is directly proportional to 1/√p based on the formula using the internal communication a dependent can be characterised by the Gilbert model. Two state Markov model signals, distance when signal strength is greater the distance should be reduced. Bayesian inference is used, few numerical examples are studied.
Keywords: Light-emitting diode (LED), Memoryless property, Birth and death process, Gilbert Model, Two-state Markov Chain, Maximum likelihood Estimation procedure (MLE) and Bayesian inference

Introduction

Study state solution of Engineering Application and optimal communication system binary data are transmitted by pulsing a laser or light-emitting diode (led) that is coupled to an optimal fiber. To transmit a binary one, we turn on the eight source for T seconds, while a binary o is represented by turning the source for the same period. Hence the signal transmitted by the optimal fiber is a series of pluses (or absence of pulses) of duration t seconds, which represents the string of binary data to be transmitted. The receiver must convert this optimal signal back into a string of binary no's. It does this photo detector.

Data input {0,1}→Laser or LED → ▭ → Photo detection electron Counter → Decision → {0,1}

Figure 1: Block diagram of an optimal communication system

The received light waves strike a photoemissive surface, which emits electrons in a random manner. While the no. of electrons emitted during a T second interval is random and thus needs to be described by a random variable, the probability mass function of that random variable changes according to the intensity of the light incident on the photoemissive surface during the T second internal.

Therefore, we define a random variable X to be the number of electrons counted during the T second interval. We describe this random variable in terms of two conditional probability mass function.

$P_{X|0}(K)=P_r(X=K|0 \text{ sent})$ (1)

In can be shown through a quantum mechanical argument that these two probability mass function should be those of Poisson variable. When a binary o is sent, a relatively low number of electrons are typically observed. Where one is sent, a higher number of electrons in typically counted.

Suppose the two probability mass function.

$P_{X|0}(K) = \frac{R^K}{k!} e^{-R_0}$, k=0,1,2,..., (2)

$$P_{X|1}(K) = \frac{R1^k}{k!} e^{-R1}, \; k=0,1,2,\ldots, \quad (3)$$

In these two parameters, R_o and R_1 are interpreted as the "average " number of electrons observed when an o is sent, and when a one is sent, respectively. Also, it is assumed that $R_0 < R_1$, so, when a o is sent we tend to observe fewer electrons that when a 1 is sent.

Gilbert Burst Model

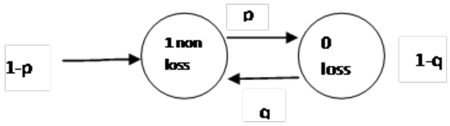

Figure 2: Gilbert Burst Loss Model

J.Pandey et. al discussed in the link lose the burst model that is the random process consisting of Bernoulli's trail which is the two-state Markov model, where 'P' is the probability that, given that, the correct pocket is delivered, given the current one is lost, p+q < 1 if p+q=1. The stationary loss probability π is given by the selection.

$$\begin{bmatrix}1-p & q\\ p & 1-q\end{bmatrix}\begin{bmatrix}1-\pi\\ \pi\end{bmatrix}=\begin{bmatrix}1-\pi\\ \pi\end{bmatrix} \text{ which implies, } \pi = \frac{p}{p+q} \quad (4)$$

The probability Pk, q a burst loss of k consecutive packets given in the occurrence loss is

$$P_k = \frac{f_k}{\sum_{k=0}^{\infty} f_k} = (1-q)^{k-1} q \quad (5)$$

Where fk=P(1-q)k-1q. Hence the burst loss probability {Pk} follows a geometric distribution using maximum likelihood estimator (MLE) of the model parameter {p,q} based on the loss burst length measurement.

Binary Communication Channel (HAMRS 1980)

$$P_k = p(\text{"e or fewer error in n trails"}) = \sum_{i=0}^{e}\binom{n}{i}(1-p)^i p^{n-i} \quad (6)$$

Consider, 'digit' received correctly (or) incorrectly. In a single error correcting Hamming code used then e=1, if assume that the transmission of the successive bit is independent, the probability of word transmission.

Link Delay Model: Gamma Distribution

The total time delay for a point to the pocket-to-pocket transmission can be written as $Y = \sum_{i=1}^{n} X_i$ where n is the total number of link, transverse by the pocket, and Xi is the time delay incurred on the i'th link, which consist of the pocket transmission time and queuing delay if the transmission path of a pocket is fixed, then the delay j is mainly due to fluctuation of the queuing delay introduced.

Materials and Methods

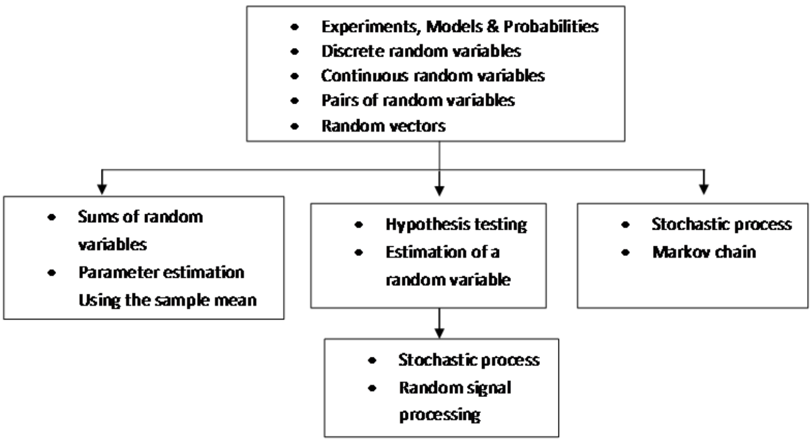

Figure 3: Block diagram of the paper

Discrete Markov Process

The real word process generally produced observable outputs that can be characterized as a signal. The signals can be discrete, such that characters from a finite alphabet qualified vectors from a code book. Otherwise continuous for example speak samples, temperature measurements. The signal source can be stationary such that its statistical properties cannot vary with time or non-stationery such that the signal properties vary over time.

The data Y = {Y_1, Y_2…,Y_l} are recorded at times t_1,t_2,…t_l ϵ {t_1,t_l} consider a system which may be described at any time has to be in one of a set of n distinct states s_1,s_2,…s_N of N=G_i Gilbert burst model we denote the actual state at time t has q, a full probabilistic description of the above systems would require specification of the current states (at time 1) as well as the predecessor states. For the special case of first-order Markov chain, this probabilities description is truncated to join the current and predecessor state.

$$P(q_i = \frac{s_j}{q_{i-1}} = s_j) \quad (7)$$

Which leads to the set of transition properties a_{ij}

$$a_{ij} = p\left\{q_i = \frac{s_i}{q_{j-1}} = s_j\right\}, \quad 1 \le i, j \le \infty \quad (8)$$

With state transition coefficient having the properties

aij ≥ 0 (9)

$$\sum_{j=1}^{n} a_{ij} \le 1 \quad (10)$$

The probability can be evaluated as,

P(0/model) = P(s_1,s_2/model)

= P(s_1).P(s_2/s_1).Ps_2.P(s_3/s_2) (11)

This probability can be evaluated as the observation sequence,

P(0/models, q_i=s_i) = a_{ij}^{d-1}(1-a_{ij})=P_1(d) (12)

The quantity P_1(d) is the discrete probability of density function duration of in state j. The exponential duration density is characteristics of the state duration in a Markov chain based on P(d) the expected number of observations in a state conditioned state ij in the state as,

$$\bar{d}_i = \sum_{d=1}^{\infty} d\, p_i(d) \quad (13)$$

$$\sum_{d=1} d\,(a)^{d-1}{}_{ij}(1-d_{ij}) = \frac{1}{1-a_{ij}} \quad (14)$$

0 = HHTTHTHTTTTM

S = 112212111221

The model is memory less process, and there is a degenerate case of a Markovian model.

Birth Death Process and Queuing System

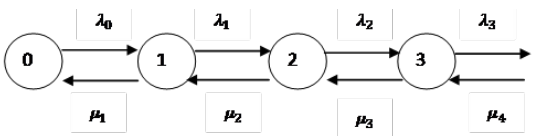

Figure 4: Birth and Death Model of a Queue

Theroem 1

For a birth-death queue with arrival rates λi and service rates μi, the stationary probabilities pi satisfy.

$$p_{i-1}\lambda_{i-1} = p_i\,\mu_i \quad \sum_{i=0}^{\infty} p_i = 1 \quad (15)$$

Proof:

We prove by induction on i that $p_{i-1}\lambda_{i-1}$ = p_i μ_i for i=1, "for an irreducible, positive recurrent continuous time Markov chain the state probabilities satisfy,

$\lim_{t\to\infty} p_j(t) = p_j$, or in vector form $\lim_{t\to\infty} p(t)=p$, where the limiting state probabilities are the unique solution to,

$$\sum_i r_{ij} = 0 \quad \text{or in vector form } p^{|}R = 0^{|} \quad (16)$$

$$\sum_j p_j = 1 \quad \text{or in vector form } p^{|}1 = 1 \quad (17)$$

Just as for the discrete-time chain, the limiting state probability p_j is the fraction of time the system spends in state j over the sample path of the process. Since r_j = -v_j and r_{ij} = q_{ij} has as nice interpretation when we write,

$$p_j v_j = \sum_{i\neq j} p_i q_{ij} \quad (18)$$

On the left side, we have the product of p_j, the fraction of time spent in stat j, and v_j the transition rate out of state j. That is, the left side is the average rate of transition out of j. Similarly on the right side $p_j q_{ij}$ is the average rate of transitions from the state I into state j. In short, the limiting state probabilities balance the average transition rate into state j against the average transition rate out of state j. Because this is balance of rates, p_{ij} as well as on the expected time 1vi that the system says in state i before the transition, $p_0\lambda_0$ = p_1 μ_1 assuming p_{i-1} λ_{i-1} = p_j μ_i its requires,

$p_i(\lambda_i + \mu_i) = p_{i-1}\lambda_{i-1} + p_{i+1}\mu_{i+1}$

From this equation the assumption that p_{i-1} λ_{i-1}= p_i μ_i implies p_i λ_i= p_{i+1} μ_{i+1}, completing this induction. For birth death process, Transient and Recurrent states for a countable infinite Markov chain, state i is recurrent if P[V_{ii}]=1; otherwise state i is transient.

Theorem 2

Consider an irreducible a periodic, finite Markov chain with transition probabilities {p_{ij}} and stationary probabilities {π_i}. For any partition of the state space into disjoint subsets S & $S^{|}$

$$\sum_{i\epsilon s}{}^{*}\sum_{j\epsilon s}\pi_i p_{ij} = \sum_{j\epsilon s}{}^{*}\sum_{i\epsilon s}\pi_j p_{ji}$$

For discrete-time queues in that it says that the average rate of transitions rate state i-1 to state i must equal the average rate of transitions from the state I to state i-1. It follows from this the theorem that stationary probability of birth-death queue has particularly simple from. At the receiver, we count the number of electrons emitted during each T second interval and then must decide whether a "0" or "1" was sent during each interval. Suppose that during a certain bit interval, it is observed that k electrons are emitted. A logical decision rule would be to calculate P_r (0 sent /X=k) and P_r (1 sent /X=k) and choose according to whichever is larger. That is, we calculate the posterior probability of each bit being sent, given the observation of the number of electrons emitted and choose the data bit, which maximizes the a posteriori probability. This is referred to as maximum a post.

Conclusion

Considering a local area computer network, a cluster of nodes connected by a common communication line. Suppose for simplicity that nodes occasionally need to transmit a message of some fixed length referred to as pocket. Also, assume that the nodes are synchronized so that time is divided into slacks, each of which is sufficiently long to support one pocket (slotted aloce). Message (pockets) are assumed to arrive according to Poisson process. Assume there are n nodes the pocket arrival assumed to be λ/n, so that the total arrival rate is each node is assune to be λ/n, So that the total arrival rate of pocket is fixed at λ packet / slacks. In slatted, allow every slat.

During each slot, one of the three events can occur.

- No node attempts to transform pockets, in which one of the slots is to be ideal.
- Exactly one node is attempt to transmit a package in which case transmission is successful more one node attempts to transmit a will need to retransmit a pocket, but if they all retransmit during the next transmit, they will continue communicating to collide and the pockets never the successfully transmitted. All nodes involved in pollution of said to be backlogged until the pocket is successfully transmitted in the allocated protocol each backlogged node chosen to transmit during the next slot.

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References

Alessandro N. Vargas. "Stability of Switching Linear Systems with Switching Signals Driven by Stochastic Processes." *Journal of the Franklin Institute*, vol. 356, no. 1, 2019, pp. 31-41.

Britto, N. and Nancy. "Bioinformatics: HIV/AIDS Epidemiology Model: Bayesian Inference." Joseph Arts and Science college, Villupuram, 2018.

Britto, N. "Functions of Block level Statistician: Cluster Mixed Farming." King Nandhivarman College of Arts and Science.

John Britto, N., Rajagopalan, V. and Sasikala, S. "Stochastic Modeling in Genetics." *National Workshop on New Trends on Stochastic process, SQC & Reliability using R*, 2019.

John Britto, N., Rajagopalan, V. and Sasikala, S. "Stochastic Process in Evolutionary Genetics; Fokker Plank Diffusion Model." St. Joseph's Arts and Science College, Cuddalore, 2019.

John Britto, N. and Muthalagi, S. "Introduction to Stochastic Models in Human Genetics." *International Journal of Research and Analytical Reviews*, 2019, pp. 167-170.

John Britto, N. "A Study on Stochastic Models for HIV infection and Aids." *International Journal of Computing Algorithm,* vol. 3, no.3, 2014, pp. 297-299.

John Britto, N. "Probability Models for Estimation of Software Reliability and Review." *International Journal of Trend in Research and Development*, 2016, pp.133-134.

John Britto, N. "Races, Genes and Intelligence: Bayesian Methodology." *International Journal of Mathematics and its Applications*, vol. 4, no. 4, 2016, pp. 123-128.

John Britto, N. "Stochastic Process and its Application Hidden Markov Chains." St. Joseph's College, Trichy, 2019.

Kailath, Thomas. “Detection of Stochastic Processes.” IEEE Transactions on Information Theory, vol. 44, no. 6, 1998, pp. 2230-2259.

Kucharczyk, D. “Stochastic Modelling as a Tool for Seismic Signals Segmentation.” *Shock and Vibration,* vol. 2016.

Kuppan, E. and Nagarajan, P. “Application of Queuing theory in Signal Processing.” *International Journal of Research and Analytical Reviews,* 2019, pp. 415-416

Yates, R.D. and Goodman, D.J. *Probability and Stochastic Process,* John Wiley & Sons, 2004.

Zhang, Yufa. “Research on Laser Coded Signal Extraction Technology based on Stochastic Resonance.” *Optik*, vol. 155, 2018, pp. 43-49.

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