2010, Vol. 24, No. 3, 468–478 DOI: 10.1214/09-BJPS104

© Brazilian Statistical Association, 2010

# Nonparametric density estimation for functional data by delta sequences

### B. L. S. Prakasa Rao

University of Hyderabad

**Abstract.** We consider the problem of estimation of density function by the method of delta sequences for functional data with values in an infinite dimensional separable Banach space.

### 1 Introduction

Methods of nonparametric estimation of density function and regression function are widely discussed in the literature starting from Prakasa Rao (1983, 1999a), Silverman (1986) and more recently in Efromovich (1999). Among the most interesting of recently developed statistical methods are those for analyzing data in the form of curves presently known as functional data. Nonparametric statistical models have been developed recently for such data. Functional data are present in many fields of application such as medicine, environmetrics, chemometrics, econometrics, etc. Analysis of such functional data is of importance in problems of classification, discrimination, regression, prediction and longitudinal studies. For an introduction to this area, see Ramsay and Silverman (2002, 2005). Gasser, Hall and Presnell (1998) consider density and mode estimation for data taking values in a normed vector space. Nonparametric regression estimation for functional data has been studied in Masry (2005), Rachdi and Vieu (2007) and Ferraty and Vieu (2006).

Our aim in this paper is to study density estimation for random elements taking values in an infinite dimensional separable Banach space such as the space of continuous functions on the interval [0, 1] endowed with the supremum norm. Examples of functional data where such spaces arise are stochastic processes with continuous sample paths on a finite interval associated with the supremum norm or stochastic processes whose sample paths are square integrable on the real line. Dabo-Niang (2004) and Dabo-Niang, Ferraty and Vieu (2006) developed a naive kernel estimator and a general kernel estimator for the estimation of a probability density function. Since there is no analog of the Lebesgue measure on a Banach space, the density function of a random element, if it exists, is related to the dominating measure with respect to which the density function or the Radon–Nikodym

Key words and phrases. Nonparametric density estimation, functional data, method of delta sequences, probability measure on a Banach space.

Received October 2008; accepted May 2009.

derivative is computed. Problems involving the density estimation of a random element taking values in a metric space were earlier studied by Geffroy (1974). Wertz (1972) and Craswell (1965) investigated the properties of kernel type density estimators for random elements taking values in locally compact topological groups [cf. Prakasa Rao (1983), page 226]. We study density estimation through the method of delta sequences generalizing the method of kernel density estimation in Dabo-Niang, Ferraty and Vieu (2006). It is known that the method of delta sequences unifies the kernel method of density estimation, histogram method and some other methods such as the method of orthogonal series for suitable choices of orthonormal bases in the one-dimensional and finite-dimensional cases. For a discussion of the method of delta sequences in the finite-dimensional cases, see Prakasa Rao (1983), pages 136–143 and pages 218–224, Walter and Blum (1979) and Susarla and Walter (1981). Density estimation for Markov processes using delta sequences is studied in Prakasa Rao (1978, 1979a) and sequential nonparametric estimation of density in the univariate case via delta sequences is investigated in Prakasa Rao (1979b). A different method of density estimation, for functional data by wavelets, was discussed recently in Prakasa Rao (2009).

Let  $\{\Omega, \mathcal{F}, P\}$  be a probability space and  $\{\mathcal{F}_t, t \geq 0\}$  be a nondecreasing family of sub- $\sigma$ -algebras of  $\mathcal{F}$ . Let  $\{W_t, t \geq 0\}$  be a standard Wiener process defined on  $\{\Omega, \mathcal{F}, P\}$  such that  $W_t$  is  $\mathcal{F}_t$ -measurable. Let C[0, T] be the space of real-valued continuous functions defined on the interval [0, T] associated with the supremum norm topology. It is known that the standard Wiener process induces a probability measure  $\mu_W$  on the space C[0, T] associated with Borel  $\sigma$ -algebra generated by the supremum norm topology. Consider a diffusion process  $\{X(t), 0 \leq t \leq T\}$  governed by the stochastic differential equation

$$dX(t) = a(t, X(t)) dt + b(t, X(t)) dW(t),$$
  $X(0) = x_0, 0 < t < T.$ 

Under some conditions on the functions  $a(\cdot, \cdot)$  and  $b(\cdot, \cdot)$ , it can be shown that the probability measure  $\mu_X$  induced by the process X on the space C[0, T] is absolutely continuous with respect to the probability measure  $\mu_W$  and one can compute the Radon-Nikodym derivative of  $\mu_X$  with respect to  $\mu_W$  by using the Girsanov's theorem. This can be considered as the probability density of the process X on the space C[0, T]. More details on such a frame work and other examples are given in Prakasa Rao (1999b). One of the motivations for analysis of functional data in our view is inference for stochastic processes [cf. Prakasa Rao (1999b, 1999c)]. We are assuming here that the complete path of the process is observable for inferential purposes. However, if the process can be observed only at discrete times either on a fine grid or when the data is sparse, other methods have to be developed as in the case of parametric inference for a discrete data, for instance, for the diffusion processes [cf. Prakasa Rao (1999b)]. Note that an important motivation for development of statistical methods for analysis of a functional data is that the parametric methods behave badly when the dimension is large or infinite due to "curse of dimensionality" and the infinite dimensional data can be viewed as a theoretical approximation of large dimensional data.

#### 2 Preliminaries

Let  $(\Omega, \mathcal{F}, P)$  be a probability space and E be an infinite dimensional separable Banach space and  $\mathcal{B}$  be the  $\sigma$ -algebra of Borel subsets of E. Suppose X is a random element defined on  $(\Omega, \mathcal{F}, P)$  taking values in  $(E, \mathcal{B})$  and that it has a density f with respect to a  $\sigma$ -finite measure  $\mu$  on  $(E, \mathcal{B})$  such that  $0 < \mu(A) < \infty$  for every open ball  $A \subset E$ . Note that

$$P(X \in A) = \int_A f(x)\mu(dx), \qquad A \in \mathcal{B}.$$

Let  $X_1, \ldots, X_n$  be independent and identically distributed random elements as X. Let  $\|\cdot\|$  denote the norm on the Banach space E. Suppose C is a compact subset of E with the property that for any  $r_n > 0$  there exist  $t_k \in E$ ,  $1 \le k \le d_n$ , where

$$C \subset \bigcup_{k=1}^{d_n} B(t_k, r_n)$$

and there exists  $\alpha_n > 0$  such that  $d_n r_n^{\alpha_n}$  is a constant c > 0. This condition gives a geometric link between the number  $d_n$  of open spheres and the radius of the  $r_n$  of the open spheres covering the compact set C [cf. Ferraty and Vieu (2008)]. Here  $B(t_k, r_n)$  denotes the open sphere with center  $t_k$  and radius  $r_n$ .

(G1) Assume that, for every  $\varepsilon > 0$ , there exists  $\gamma > 0$  such that

$$|f(y)-f(x)|\leq \varepsilon \qquad \text{if } \|y-x\|\leq \gamma, x\in C, y\in E.$$

Note that this condition is stronger than the uniform continuity of the function f on C as it refers to  $x \in C$  and  $y \in E$ . It follows, in particular, that there exists a postive constant M such that

$$\sup_{x \in C} f(x) \le M < \infty.$$

**Definition.** A sequence of nonnegative functions  $\{\delta_m(x, y), m \ge 1\}$  defined on  $E \times E$  is said to be a *delta sequence* with respect to the measure  $\mu$  if the following conditions hold:

(G2) for every  $\gamma$ ,  $0 < \gamma \le \infty$ ,

$$\lim_{m\to\infty} \sup_{x\in C} \left| \int_{[y:\|y-x\|\leq \gamma]} \delta_m(x,y) \mu(dy) - 1 \right| = 0;$$

(G3) there exists a constant  $c_0 > 0$  such that

$$\sup_{x\in C, y\in E} \delta_m(x, y) \le c_0 s_m < \infty,$$

where  $0 < s_m \to \infty$  as  $m \to \infty$  and  $\lim_{m \to \infty} \frac{m}{s_m \log m} = \infty$ ;

(G4) there exist c > 0,  $\beta_1 > 0$  and  $\beta_2 > 0$  such that

$$|\delta_m(x_1, y) - \delta_m(x_2, y)| \le c s_m^{\beta_2} ||x_1 - x_2||^{\beta_1}$$

for all  $x_1, x_2, y \in E$ ; and

(G5) for any  $\gamma > 0$ ,

$$\lim_{m \to \infty} \sup_{(x,y) \in C \times [y: ||y-x|| > \gamma]} \delta_m(x,y) ||y-x|| = 0.$$

Further suppose that

(G6)  $d_n = n^{\alpha}, \alpha > 0$ , and

$$r_n^{\beta_1} s_m^{\beta_2} < ([s_m \log m]/m)^{1/2}$$

for large m and n.

Let

$$f_n(x) = \frac{1}{n} \sum_{i=1}^n \delta_m(x, X_i).$$

The choice of the sequence m might depend on n such that  $m \to \infty$  as  $n \to \infty$ .

We now prove the following result leading to uniform strong consistency of the estimator  $f_n(x)$  over the set C as an estimator of f(x).

**Theorem 1.** Suppose that  $m \to \infty$  and there exists  $0 such that <math>n^p \le m \le n$  for n large. Under the conditions (G1)–(G6),

$$\lim_{n \to \infty} \sup_{x \in C} |f_n(x) - f(x)| = 0 \qquad a.s.$$

**Proof.** Let  $\gamma > 0$  and  $x \in C$ . Define

$$I_1(x) = \int_{[y:\|y-x\| \le \gamma]} \delta_m(x, y) (f(y) - f(x)) \mu(dy)$$
 (2.1)

and

$$I_2(x) = \int_{[y:\|y-x\|>\gamma]} \delta_m(x,y) (f(y) - f(x)) \mu(dy). \tag{2.2}$$

Observe that

$$E[f_n(x)] - f(x) = \int_E \delta_m(x, y) f(y) \mu(dy) - f(x)$$
 (2.3)

and hence

$$E[f_{n}(x)] - f(x) - I_{1}(x) - I_{2}(x)$$

$$= \int_{E} \delta_{m}(x, y) f(y) \mu(dy) - f(x) - \int_{E} \delta_{m}(x, y) (f(y) - f(x)) \mu(dy)$$

$$= f(x) \left[ \int_{E} \delta_{m}(x, y) \mu(dy) - 1 \right].$$
(2.4)

Observe that

$$\lim_{m \to \infty} \sup_{x \in C} \left| \int_{E} \delta_{m}(x, y) \mu(dy) - 1 \right| = 0$$

by (G2). Hence

$$\lim_{n \to \infty} \sup_{x \in C} |E[f_n(x)] - f(x) - I_1(x) - I_2(x)| = 0$$
 (2.5)

by the conditions (G1) and (G2). Furthermore, for every  $x \in C$ ,

$$|I_{2}(x)| \leq \int_{[y:\|y-x\|>\gamma]} \delta_{m}(x,y) f(y) \mu(dy)$$

$$+ f(x) \int_{[y:\|y-x\|>\gamma]} \delta_{m}(x,y) \mu(dy)$$

$$= \int_{[y:\|y-x\|>\gamma]} \delta_{m}(x,y) \frac{\|y-x\|}{\|y-x\|} f(y) \mu(dy)$$

$$+ f(x) \int_{[y:\|y-x\|>\gamma]} \delta_{m}(x,y) \mu(dy)$$

$$\leq \frac{1}{\gamma} \sup_{(x,y) \in C \times [y:\|y-x\|>\gamma]} [\delta_{m}(x,y) \|y-x\|] \int_{[y:\|y-x\|>\gamma]} f(y) \mu(dy)$$

$$+ f(x) \int_{[y:\|y-x\|>\gamma]} \delta_{m}(x,y) \mu(dy)$$

$$\leq \frac{1}{\gamma} \sup_{(x,y) \in C \times [y:\|y-x\|>\gamma]} [\delta_{m}(x,y) \|y-x\|]$$

$$+ M \sup_{x \in C} \int_{[y:\|y-x\|>\gamma]} \delta_{m}(x,y) \mu(dy)$$

$$+ M \sup_{x \in C} \int_{[y:\|y-x\|>\gamma]} \delta_{m}(x,y) \mu(dy)$$

which implies that

$$\sup_{x \in C} |I_2(x)|$$

$$\leq \frac{1}{\gamma} \sup_{(x,y) \in C \times [y: \|y-x\| > \gamma]} [\delta_m(x,y) \|y-x\|]$$

$$+ M \sup_{x \in C} \int_{[y: \|y-x\| > \gamma]} \delta_m(x,y) \mu(dy).$$

Assumptions (G2) and (G5) imply that the two terms on the right-hand side of the above inequality tend to zero as  $m \to \infty$ .

Note that, for every  $\varepsilon > 0$ , there exists  $\gamma > 0$  such that

$$|f(y)-f(x)| \leq \varepsilon \qquad \text{if } \|y-x\| \leq \gamma, x \in C, y \in E$$

by condition (G1). Then there exists  $\gamma > 0$  such that

$$|I_1(x)| \le \varepsilon \int_{[y:\|y-x\| \le \gamma]} \delta_m(x,y) \mu(dy). \tag{2.7}$$

Hence

$$\sup_{x \in C} |I_1(x)| \le \varepsilon \sup_{x \in C} \left| \int_{[y:\|y-x\| \le \gamma]} \delta_m(x, y) \mu(dy) \right|$$

and the term on the right-hand side can be made smaller than  $2\varepsilon$  as  $m \to \infty$  by condition (G2). Therefore

$$\lim_{n \to \infty} \sup_{x \in C} |E[f_n(x)] - f(x)| = 0.$$
 (2.8)

We now prove that

$$\lim_{n \to \infty} \sup_{x \in C} |f_n(x) - E[f_n(x)]| = 0 \quad \text{a.s.}$$

Let  $x \in C$ . Then

$$f_n(x) - E[f_n(x)] = \frac{1}{n} \sum_{i=1}^n Z_{i,x},$$

where

$$Z_{i,x} = \delta_m(x, X_i) - E[\delta_m(x, X_i)].$$

Note that  $Z_{i,x}$ ,  $1 \le i \le n$ , are independent and identically distributed real-valued bounded random variables bounded by  $2c_0s_m$  by condition (G3). Applying the Bernstein's inequality [see Hoeffding (1963); Prakasa Rao (1983), page 183], we get that, for any  $\eta > 0$  and m large,

$$P\left[|f_{n}(x) - E[f_{n}(x)]| > \eta \sqrt{\frac{s_{m} \log m}{m}}\right]$$

$$\leq 2 \exp\left[-\frac{n((s_{m} \log m)/m)\eta^{2}}{4c_{0}Ms_{m} + 4c_{0}s_{m}\eta\sqrt{(s_{m} \log m)/m}}\right]$$

$$\leq 2 \exp\left[-\frac{\eta^{2}n \log m/m}{8c_{0}M}\right].$$
(2.9)

Since the set  $C \subset C_n = \bigcup_{k=1}^{d_n} B(t_k, r_n)$ , for any  $x \in C$ , there exists an index  $\tau(x)$  among  $t_1, \ldots, t_{d_n}$  such that  $x \in B(t_{\tau(x)}, r_n)$ . Hence

$$P\left[\sup_{x\in C} |f_n(x) - E[f_n(x)]| > 2\eta\sqrt{\frac{s_m \log m}{m}}\right]$$

$$\leq P\left[\sup_{x\in C} |f_n(x) - E[f_n(x)]\right] \tag{2.10}$$

$$- f_n(t_{\tau(x)}) + E[f_n(t_{\tau(x)})]| > \eta \sqrt{\frac{s_m \log m}{m}}$$

$$+ P\left[\max_{1 \le k \le d_n} |f_n(t_k) - E[f_n(t_k)]| > \eta \sqrt{\frac{s_m \log m}{m}}\right].$$

Conditions (G4) and (G6) imply that

$$\sup_{x \in C} |f_n(x) - f_n(t_{\tau(x)})| \le O(r_n^{\beta_1} s_m^{\beta_2}) = O\left(\sqrt{\frac{s_m \log m}{m}}\right).$$

Hence, for some  $\eta > 0$  and for sufficiently large n and large m

$$P\left[\sup_{x\in C} |f_n(x) - E[f_n(x)] - f_n(t_{\tau(x)}) + E[f_n(t_{\tau(x)})]| > \eta \sqrt{\frac{s_m \log m}{m}}\right] = 0.$$

Therefore,

$$P\left[\sup_{x\in C}|f_n(x) - E[f_n(x)]| > \eta\sqrt{\frac{s_m\log m}{m}}\right] \le 2d_n\exp\left[-\frac{\eta^2n\log m/m}{8c_0M}\right].$$

Since  $m \le n$  and  $\log m \ge p \log n$ , it follows that there exists  $\eta > 0$  such that

$$P\left[\sup_{x\in C}|f_n(x) - E[f_n(x)]| > \eta\sqrt{\frac{s_m\log m}{m}}\right] \le n^{\alpha - p\eta^2/C_1}$$

for some positive constant  $C_1$ . Applying the Borel–Cantelli lemma, we get that

$$\sup_{x \in C} |f_n(x) - E[f_n(x)]| = O\left(\sqrt{\frac{s_m \log m}{m}}\right) \quad \text{a.s.}$$

Since

$$\frac{s_m \log m}{m} \to 0 \quad \text{as } m \to \infty,$$

we obtain that

$$\sup_{x \in C} |f_n(x) - E[f_n(x)]| \to 0 \quad \text{a.s. as } n \to \infty.$$
 (2.11)

Combining equations (2.8) and (2.11), we obtain that

$$\sup_{x \in C} |f_n(x) - f(x)| \to 0 \quad \text{a.s. as } n \to \infty.$$
 (2.12)

**Theorem 2.** Suppose conditions (G1) and (G3)–(G6) hold. In addition, suppose that the following condition holds: for every  $\gamma$ ,  $0 \le \gamma \le \infty$ ,

(G2)'

$$\sup_{x \in C} \left| \int_{[y:\|y-x\| \le \gamma]} \delta_m(x, y) \mu(dy) - 1 \right| = O(D_m),$$

where  $D_m = \sup\{\|y - x\|; x \in C, y \in E, \delta_m(x, y) > 0\} = o(1)$  as  $m \to \infty$ . Further suppose that f is Lipschitzian in the sense that there exists a constant K > 0 such that

$$|f(x) - f(y)| \le K||x - y||$$

for any  $x \in C$ ,  $y \in E$ . Then, with probability one,

$$\sup_{x \in C} |f_n(x) - f(x)| = O(D_m) + O\left(\sqrt{\frac{s_m \log m}{m}}\right). \tag{2.13}$$

**Proof.** Since (G2)' implies (G2), applying Theorem 1, we get that

$$\sup_{x \in C} |f_n(x) - E[f_n(x)]| = O\left(\sqrt{\frac{s_m \log m}{m}}\right) \quad \text{a.s.}$$

It is sufficient to prove that

$$\sup_{x \in C} |E[f_n(x)] - f(x)| = O(D_m).$$

Note that

$$Ef_n(x) - f(x) = \int_E \delta_m(x, y) f(y) \mu(dy) - f(x)$$

$$= \int_E \delta_m(x, y) (f(y) - f(x)) \mu(dy)$$

$$+ \int_E \delta_m(x, y) f(x) \mu(dy) - f(x)$$

$$= J + f(x) \left[ \int_E \delta_m(x, y) \mu(dy) - 1 \right],$$
(2.14)

where

$$J = \int_{F} \delta_{m}(x, y) (f(y) - f(x)) \mu(dy).$$

Hence

$$|Ef_n(x) - f(x) - J| = O(D_m)$$
 (2.15)

by condition (G2)'. Since f satisfies the condition that there exists a constant K such that

$$|f(x) - f(y)| \le K||y - x||$$

for all  $x \in C$ ,  $y \in E$ , it follows that

$$|J| \le \int_{E} \delta_{m}(x, y)|f(y) - f(x)|\mu(dy)$$

$$\le K D_{m} \int_{E} \delta_{m}(x, y)\mu(dy)$$

$$\le O(D_{m})$$
(2.16)

by condition (G2)'. Combining equations (2.15) and (2.16), we get the relation

$$|Ef_n(x) - f(x)| = O(D_m).$$
 (2.17)

**Remarks 1.** Let  $C_0[0, 1]$  be the space of real-valued continuous functions  $x(\cdot)$  on the interval [0, 1] with x(0) = 0. Suppose the space  $C_0[0, 1]$  is equipped with uniform topology induced by the norm

$$||x|| = \sup_{t \in [0,1]} |x(t)|.$$

Let  $\mu(\cdot)$  denote the Wiener measure on the space  $C_0[0, 1]$  induced by the standard Wiener process and  $B_m^x$  be the closed ball with center  $x \in C_0[0, 1]$  and radius  $\frac{1}{m}$ . Define

$$\delta_m(x, y) = \frac{1}{\mu(B_m^x)} I(y \in B_m^x), \tag{2.18}$$

where I(A) denotes the indicator function of the set A. It is easy to check that the corresponding density estimator  $f_n(x)$  is the naive kernel estimator proposed in equation (6) in Dabo-Niang (2004). This sequence clearly satisfies condition (G2).

Suppose  $a_n^x$  is a sequence of positive numbers. Let

$$\delta_m(x, y) = \frac{1}{a_n^x} K_n(\|x - y\|), \tag{2.19}$$

where  $K_n(\cdot)$  is sequence of functions satisfying conditions (H2)–(H6) in Dabo-Niang, Ferraty and Vieu (2006). As was indicated earlier, the choice of the sequence m may depend on n such that  $m \to \infty$  as  $n \to \infty$ . Then we get the kernel estimator proposed by them. Other estimators using delta sequences can be constructed following the ideas in Example 2.8.3 in Prakasa Rao (1983), page 136, depending on the space E and the measure  $\mu$ .

**Remarks 2.** It is true that conditions (G2)–(G6) are patterned on a similar set of conditions for kernel type of estimators but, due to the infinite dimensional nature of the problem, additional conditions are necessary to obtain uniform consistency even over compact sets. In a recent note, Ferrarty and Vieu (2008) comment on the

conditions for deriving uniform consistency on compact sets. In particular, they suggest that the conditions on the infinite dimensional spaces should be such that the compact set C satisfies the property

$$C \subset \bigcup_{k=1}^{\tau} B(t_k, \ell),$$

where the number  $\tau$  of spheres and the radius  $\ell$  satisfy the geometric link condition  $\tau \ell^{\alpha} = c$  for some  $\alpha > 0$  and c > 0. This condition holds trivially for any finite dimensional Euclidean space but it also holds for infinite dimensional projection-based metric spaces. Here  $B(t_k,\ell)$  is the open sphere with center  $t_k$  and radius  $\ell$ . Condition (G3) relates to the bound on  $\delta_m$  over  $C \times E$  and condition (G4) relates to the uniform Lipschitzian property of  $\delta_m(x,y)$ . The choice  $\beta_1$  and  $\beta_2$  are governed by condition (G6) involving  $r_n$  and  $s_m$ . Condition (G5) is a condition on the limiting behavior of  $\delta_m(x,y)\|x-y\|$  as m tends to infinity and it is not a condition on the bound of  $\sup \|x-y\|$  over  $C \times C$ . Condition (G6) is introduced to get a rate of convergence for uniform consistency.

## References

Craswell, K. J. (1965). Density estimation in a topological group. *Annals of Mathematical Statistics* **36** 1047–1048. MR0178529

Dabo-Niang, S. (2004). Kernel density estimator in an infinite-dimensional space with a rate of convergence in the case of diffusion process. *Applied Mathematics Letters* **17** 381–386. MR2045741

Dabo-Niang, S., Ferraty, F. and Vieu, P. (2006). Mode estimation for functional random variable and its application for curve classification. Far East Journal of Theoretical Statistics 18 93–119. MR2200256

Efromovich, S. (1999). Nonparametric Curve Estimation: Methods, Theory and Applications. Springer, New York. MR1705298

Ferraty, F. and Vieu, P. (2006). *Nonparametric Functional Data Analysis: Theory and Practice*. Springer, New York. MR2229687

Ferraty, F. and Vieu, P. (2008). Erratum of: 'Non-parametric models for functional data, with application in regression, time-series prediction and curve estimation.' *Journal of Nonparametric Statistics* **20** 187–189. MR2407965

Gasser, T., Hall, P. and Presnell, B. (1998). Nonparametric estimation of the mode of a distribution of random curves. *Journal of the Royal Statistical Society Series B. Statistical Methodology* 60 681–691. MR1649539

Geffroy, J. (1974). Sur l'estimation d'une densite dans un espace metrique. C. R. Acad. Sci. Paris Ser. A-B 278 A 1449–1452. MR0341733

Hoeffding, W. (1963). Probability inequalities for sums of bounded random variables. *Journal of the American Statistical Association* **58** 13–30. MR0144363

Masry, E. (2005). Nonparametric regression estimation for dependent functional data; asymptotic normality. *Stochastic Processes and Their Applications* **115** 155–177. MR2105373

Prakasa Rao, B. L. S. (1978). Density estimation for Markov processes using delta sequences. *Annals of the Institute of Statistical Mathematics* **30** 321–328. MR0514500

Prakasa Rao, B. L. S. (1979a). Nonparametric estimation for continuous time Markov processes via delta families. Publications de l'Institut de Statistique de l'Université de Paris 24 79–97. MR0561817

- Prakasa Rao, B. L. S. (1979b). Sequential nonparametric estimation of density via delta sequences. Sankhyā, Series A 41 82–94. MR0615042
- Prakasa Rao, B. L. S. (1983). Nonparametric Functional Estimation. Academic Press, New York. MR0740865
- Prakasa Rao, B. L. S. (1999a). Nonparametric functional estimation: an overview. In Asymptotics, Nonparametrics and Time Series (S. Ghosh, ed.) 461–509. Marcel Dekker, New York. MR1724706
- Prakasa Rao, B. L. S. (1999b). Statistical Inference for Diffusion Type Processes. Arnold, London and Oxford Univ. Press, New York.
- Prakasa Rao, B. L. S. (1999c). *Semimartingales and Their Statistical Inference*. Chapman and Hall, London and CRC Press, Boca Raton.
- Prakasa Rao, B. L. S. (2009). Nonparametric estimation for functional data via wavelets. *Communications in Statistics—Theory and Methods: Special Issue in Honor of Prof. M. Akahira*. To appear.
- Rachdi, M and Vieu, P. (2007). Nonparametric regression for functional data: automatic smoothing parameter selection. *Journal Statistical Planning and Inference* **137** 2784–2801. MR2323791
- Ramsay, J. and Silverman, B. W. (2005). Functional Data Analysis. Springer, New York. MR2168993
- Ramsay, J. and Silverman, B. W. (2002). Applied Functional Data Analysis: Methods and Case Studies. Springer, New York. MR1910407
- Silverman, B. W. (1986). Density Estimation and Data Analysis. Chapman and Hall, London. MR0848134
- Susarla, V. and Walter, G. (1981). Estimation of a multivariate density function using delta sequences. The Annals of Statistics 9 347–355. MR0606618
- Walter, G. and Blum, G. J. (1979). Probability density estimation using delta sequences. The Annals of Statistics 7 328–340. MR0520243
- Wertz, W. (1972). Schatzfolgen fur dichten aub topolgischen gruppen. Operation Res. Verfahren 14 247–257.

University of Hyderabad Gachibowli, Hyderabad 500046 India

E-mail: blsprao@gmail.com