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**Density estimation for mixed Euclidean and non-Euclidean data in the presence of measurement error. (English summary)**

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Recently non-Euclidean data (e.g., circular data, spherical data) have gathered interest in statistics. As with Euclidean data, non-Euclidean data sometimes contain measurement errors. This article is concerned with the problem of estimating a joint density for contaminated Euclidean and non-Euclidean data.

Suppose that we are interested in estimating the unknown joint density of  $X = (X_1, X_2)$  nonparametrically, where  $X_1 \in \mathbb{R}^d$  and  $X_2 \in \mathbb{G}_C$  are Euclidean and non-Euclidean components, respectively, and where  $\mathbb{G}_C$  is a finite-dimensional compact and connected Lie group equipped with a group operation  $\circ$ . Also suppose that we can only observe contaminated data  $Z = (Z_1, Z_2) = (U_1 + X_1, U_2 \circ X_2)$ , where  $U = (U_1, U_2)$  is an unobservable measurement error that is assumed to satisfy  $X \perp U$  and  $U_1 \perp U_2$ . For identification purposes of the density of  $X$ , it is also assumed that distributions of both  $U_1$  and  $U_2$  are known. Under this setup, a new deconvolution density estimator is proposed. The estimator consists of a deconvolution kernel density estimator for the Euclidean component and a Fourier series estimator for the non-Euclidean component. The weight function that constructs the deconvolution density estimator is shown to have the unbiased scoring property, which eliminates the effect of the measurement error  $U$  in the bias part.

Asymptotic properties of the deconvolution density estimator are explored extensively. These include rates of convergence for the cases of  $L^2$ , pointwise and uniform convergences and asymptotic normality depending on a few different smoothness scenarios. New proof techniques based on Fourier analysis on topological groups that are used for derivations of such convergence results are also of independent interest. Usefulness of the estimator is illustrated in the simulation study and a real data analysis on the joint density estimation for bivariate mismeasured data of the level of sulfur dioxide ( $\text{SO}_2$ ) and wind direction.

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*Note: This list reflects references listed in the original paper as accurately as possible with no attempt to correct errors.*