LPiTrack Signal Processing Algorithm and Application to Biometric Identification

DEEP Mukhopadhyay and Shinjini Nandi

Temple University, Department of Statistics

Philadelphia, Pennsylvania, 19122, U.S.A.

http://sites.temple.edu/deepstat/

Best Paper Award, JSM 2016 Section on Statistical Computing of ASA.

Winner of 2014 IEEE International Biometric Competition.

Outline

Motivation

The study of eye movement patterns gaining increasing importance as modes of scientific inquiry. It has been used as a primary tool to answer important research questions arising in various fields:

- Marketing (Pieters, 2008, Teixeira et al., 2012)
- Psychology (Frank et al., 2014)
- Neuroscience (Anderson and MacAskill, 2013, Pereira et al., 2014)
- Biometrics (Kasprowski and Ober, 2012)
- Google Glass [1]

⋮ ⋮ ⋮

[1] http://glassalmanac.com/google-patents-eye-tracking-technology-glass/2426/

Goal

1. We proposes a *generic* nonparametric statistical modeling scheme called `LPiTrack` for eye-movement trajectory data analysis and compression.

2. We then apply that general algorithm for automated biometric identification (differentiate or identify or authenticate individuals) by mining distinctive eye movement patterns.

How can we use human eye movement dynamics to establish the identity of an individual? How to design such automated recognition system, which is computationally efficient, highly scalable (for large-scale implementation) and has a strong theoretical basis?

Current Practice

The development of SMART computational models for eye movement signal processing is still in its infancy.

Mostly based on primitive features (Holland and Komogortsev, 2013, Kasprowski and Ober, 2004) like total looking time, total number of fixations (i.e. the total number of fixations that met the ≥ 100 msec criterion), average velocity, average spatial location, average horizontal and vertical velocities etc. Simola et al. (2008) described temporal techniques based on hidden Markov models usually applied on gaze velocity/acceleration.

The Missing Piece

There exist striking *disconnects*, *conceptually and algorithmically, among these various 'isolated' naive methods*; thus, not surprisingly, despite more than a decade of research, very little is known about *unified statistical algorithms* for designing an automated biometric recognition system.

More importantly, we are interested in developing a nonparametric algorithm that can systematically learn the representations of eye movement trajectories.

Data Structure

The dataset is composed of 1430 samples recorded for 34 subjects. Every sample consists of eye movement recordings registered when a person observed an image. Every subject looked at several (20 to 50) different photographs. The modeling task is **identify subjects** (# class =34) based on their eye movement trajectories.

Kasprowski and Harezlak (2014) referred this data set as "*one of the most challenging datasets used for eye movement biometrics so far.*"

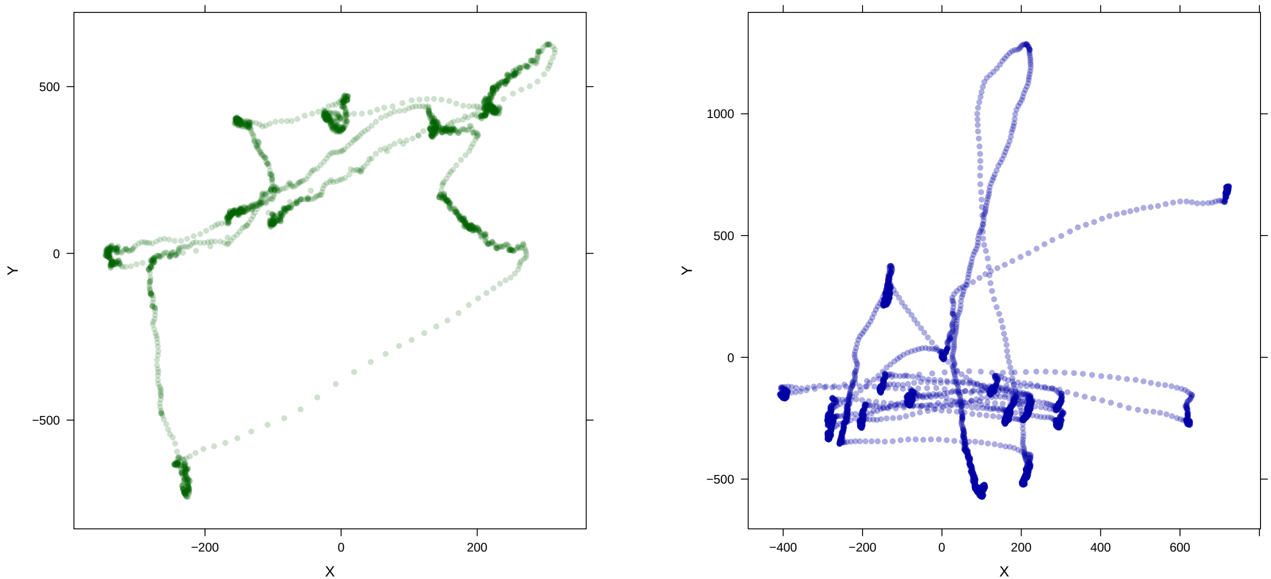


Figure 1: Eye Trajectory for subject id #19 on left and right plot for sub id #15. Spatial fixation regions have been highlighted. Clearly, the trajectories are of different lengths. The `LPiTrack` algorithm aims to learn the patterns to identify the individuals.

Sub.id	Eye Gaze Points								
s1	x	703.72	702.63	$\cdots$	-200.82				
	y	-259.22	-261.6	$\cdots$	-84.94				
s2	x	-60.23	-58.61	$\cdots$	69.38	$\cdots$	88.58	$\cdots$	15.56
	y	-839.59	839.29	$\cdots$	155.07	$\cdots$	94.16	$\cdots$	-339.91
$\vdots$			$\vdots$	$\ldots$	$\vdots$	$\ldots$	$\vdots$		
s34	x	-582.25	-581.16	$\cdots$	-52.36	$\cdots$	274.11		
	y	-1169.1	-1168.5	$\cdots$	-783.43	$\cdots$	-575.76		

Trajectories are of DIFFERENT LENGTHS, vary from 891 to $22,012$. Machine learning tools are *NOT directly applicable* in this raw format. The solution lies in efficiently representing these non-standard trajectory data by means of “statistical parameters”–**Representation Learning**.

Concept 1. LP Transform Coding

The foundation of our algorithm is based on LP orthonormal representation of stochastic processes in Hilbert space.

Theorem

Let $\{X(t), t \in \mathbb{T}\}$, $\mathbb{T}$ being index set of interest be any arbitrary(non-Gaussian discrete or continuous) zero-mean random process with finite second order moments. Then $\{X(t)\}$ can be represented as follows (that converges in L_2 sense in the corresponding Hilbert functional space)

$$X(t) \;=\; \sum_{j=1}^{\infty} \mathrm{LP}[j; X(t)]\; T_j[X](t), \tag{1}$$

where $\{T_j[X](t), j \in \mathbb{N}\}$ are the LP polynomial basis functions, especially designed rank-transform based orthogonal function for the underlying process.

Historical Significance

The idea of approximating a stochastic process by a linear combination of orthogonal polynomials with random coefficients was first observed by Wiener (1938), famously known as *Wiener polynomial chaos*. Wiener used Hermite polynomials to model Gaussian process. Hermite polynomial based approximation for Gaussian process achieves the optimal convergence (Cameron-Martin theorem), in fact, the rate is exponential. *However if we have non-Gaussian process this representation is non-optimal and convergence rate may be substantially slower.*

Our result can be viewed as a <u>Nonparametric Generalization</u> of Wiener's idea for any square-integrable random function $X(t)$.

Concept 2. LPTime

The trajectories are (i) extremely non-Gaussian, (ii) non-linear, and (iii) bi-variate (X-Y dynamics). How to proceed?

Definition

Transform $X(t)$ into $\text{Vec}(T[X])(t) = \{T_1[X](t), \ldots, T_m[X](t)\}$. `LPTime` procedure models nonlinear process by specifying ℓth order vector autoregressive (VAR) of the following form:

$$\text{Vec}(T[X])(t) = \sum_{k=1}^{l} A(k;\, l)\text{Vec}(T[X])(t-k) + \epsilon(t) \qquad (2)$$

where $A(k;\, l)$ are $(m \times m)$ time-variant coefficient matrices and $\epsilon(t)$ is multivariate centered Gaussian white noise with covariance Σ_ϵ. This system describes the desired *joint dynamics*.

Concept 3. LP Spatial Copula

We capture the eye-fixation or clustering patterns *using copula density* that compactly represent the spatial dependence (X, Y). Current parametric families of copulas are *inadequate for our purpose* as we would like to allow arbitrary dependence of the underlying spatial random process $Z(x, y)$.

Definition

Compute LP-comoments spatial matrix

$$\mathrm{LP}[j, k;\; X,\; Y] = \mathbb{E}[T_j(X;\; X)T_k(Y;\; Y)] \text{ for } j, k > 0 \tag{3}$$

which are orthogonal coefficients of copula density

$$\mathrm{cop}(u, v; X, Y) - 1 = \sum_{j,k>0} \mathrm{LP}(j, k; X, Y) T_j\left[Q(u; X)\right] T_k\left[Q(v; Y)\right]$$

Concept 4. LP Shape Detector

The *shapes* of the X and Y coordinates distributions are clearly informative. How to uniquely characterize the *shape of the distribution* in a robust way. Moments do not uniquely characterize (Heyde, 1963) the probability distribution + highly susceptible to extreme observations, not a robust signature.

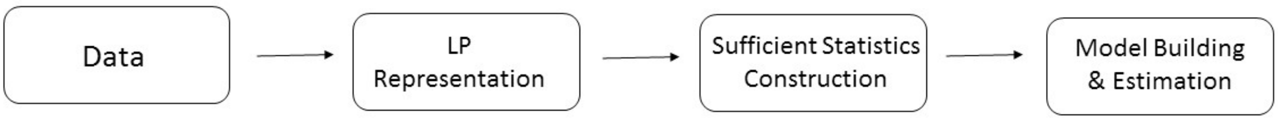
Definition

For a random variable X define

$$\mathrm{LP}[j;X] \equiv \mathrm{LP}(j,0;X,X) = \mathrm{Cor}[X, T_j(X;X)], \text{ for } j>0, \quad (4)$$

which are the "coordinate" of the random variable X in the LP Hilbert functional space.

Concept 5. LP Representation Learning

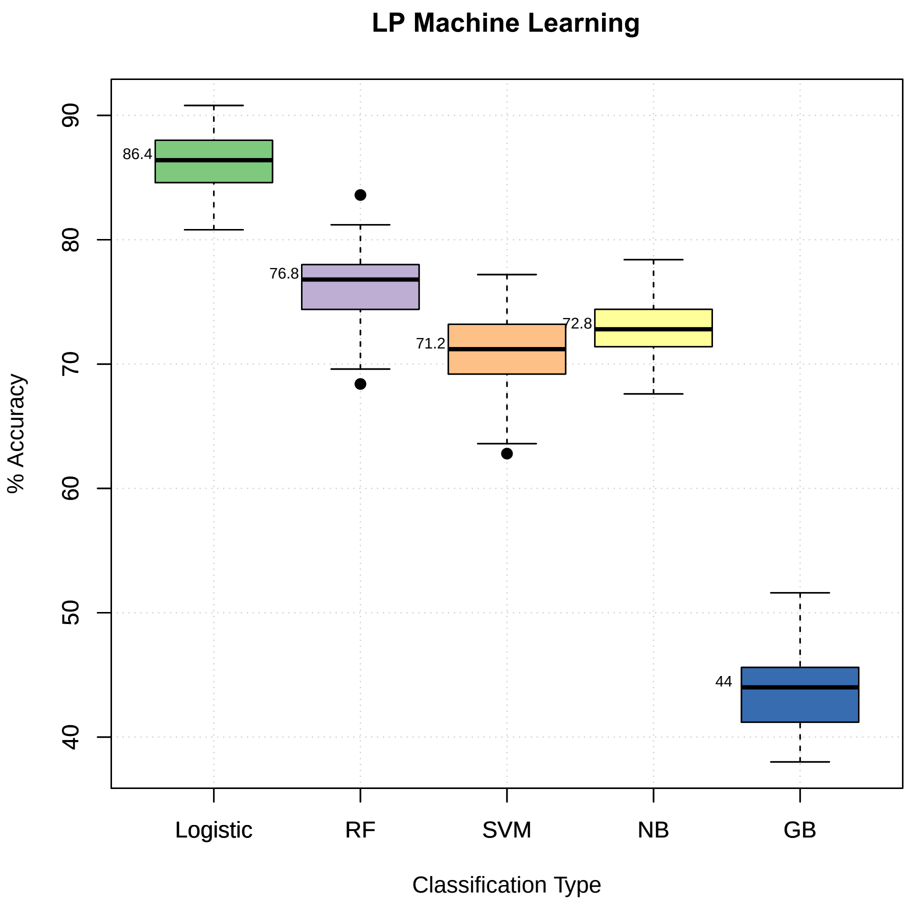


Mukhopadhyay and Parzen (2014): "*What comes first - a parametric model or sufficient statistics?*" Unlike traditional statistical modeling we first converts data into sufficient statistics and then constructs model.

Performance

We applied the `LPiTrack` algorithm on the dataset provided for the second Eye Movements Verification and Identification Competition (EMVIC) organized as a part of 2014 International Joint Conference on Biometrics (IJCB).

Classification with 34 classes based on the LP Transformed features.


LP Machine Learning
% Accuracy
90
80
70
60
50
40
86.4
76.8
71.2
72.8
44
Logistic
RF
SVM
NB
GB
Classification Type

Contest Validation set

- A fixed hold-out (unlabeled) test set representing 41% of the original data was retained for evaluation by officials of 2014 IEEE Biometrics Council.
- Number of competing algorithms were **82**!
- Our proposed algorithm was able to correctly identify 81.5% of the individuals. Winner.

Conclusion: Our EMVIC data analysis shows that there is a genuine promise of using eye movement characteristics as a biometric feature. This 'personalized unique' eye movement patterns can be exploited for other purposes like early detection of Alzheimer's disease or measuring the effectiveness of TV commercials and many others.

CRAN - Package LPTime

LPTime: LP Nonparametric Approach to Non-Gaussian Non-Linear Time Series Modelling

Specially designed rank transform based Legendre Polynomial-like (LP) orthonormal transformations are implemented for non-linear signal processing.

Version:	1.0-2
Depends:	orthopolynom
Suggests:	lattice
Published:	2015-03-03
Author:	Subhadeep Mukhopadhyay, Shinjini Nandi
Maintainer:	Shinjini Nandi <shinjini.nandi at temple.edu>
License:	GPL-2 | GPL-3 [expanded from: GPL (≥ 2)]
URL:	http://sites.temple.edu/deepstat/d-products/
NeedsCompilation:	no
CRAN checks:	LPTime results

Downloads:

Reference manual:	LPTime.pdf
Package source:	LPTime_1.0-2.tar.gz
Windows binaries:	r-devel: LPTime_1.0-2.zip, r-release: LPTime_1.0-2.zip, r-oldrel: LPTime_1.0-2.zip
OS X Snow Leopard binaries:	r-release: LPTime_1.0-2.tgz, r-oldrel: LPTime_1.0-2.tgz
OS X Mavericks binaries:	r-release: LPTime_1.0-2.tgz

We have an R-package. Go check it out!

Acknowledgements

Our special thanks to **Dr. Richard Heiberger** for providing us many valuable computational tips to make `LPiTrack` a powerful fast algorithm that researchers from different fields can routinely use for mining eye-movement data.

Bibliography

Kasprowski, P. and Harezlak, K. (2014). The second eye movements verication and identication competition. *2014 IEEE International Joint Conference on Biometrics* 1-6.

Kasprowski, P. and Ober, J. (2004a). Eye movements in biometrics. In *Biometric Authentication. Springer*, 248-258.

Kasprowski, P. and Ober, J. (2004b). Eye movements in biometrics. In *Biometric Authentication. Springer*, 248-258.

Mukhopadhyay, S. and Parzen, E. (2014a). LP approach to statistical modeling. Unpublished Technical Report available at *arXiv:1405.2601.*

Mukhopadhyay, S. and Parzen, E. (2014b). Nonlinear Time Series modeling by LPTime, Nonparametric Empirical Learning. *arXiv:1308.0642.*

Mukhopadhyay, S., Parzen, E. and Lahiri, S. N. (2012). From data to constraints. *Bayesian Inference And Maximum Entropy Methods In Science And Engineering: 31st International Workshop, Waterloo, Canada*, **1443** 32-39.

Parzen, E. and Mukhopadhyay, S. (2013). United Statistical Algorithms, LP comoment, Copula Density, Nonparametric Modeling. *59th ISI World Statistics Congress (WSC), Hong Kong.*

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of Royal Statistical Society: Series B*, **58** 267-288.