scch
software competence center
hagenberg

FUZZY.LOGIC.LAB.LINZ

Advances in Knowledge-Based Technologies

Proceedings of the
Master and PhD Seminar
Sommer term 2014, part 2

Softwarepark Hagenberg
SCCH, Room 0/2
3 July 2014

Software Competence Center Hagenberg
Softwarepark 21
A-4232 Hagenberg
Tel. +43 7236 3343 800
Fax +43 7236 3343 888
www.scch.at

Fuzzy Logic Laboratorium Linz
Softwarepark 21
A-4232 Hagenberg
Tel. +43 7236 3343 431
Fax +43 7236 3343 434
www.flll.jku.at

Program

Session 1. Chair: Susanne Saminger-Platz

9:30	Bernhard Moser:
	On Metric Equivalence for Event-Based Signal Processing
10:00	Werner Reisner:
	On Modelling Visual Discomfort for Stereoscopic Images

Session 2. Chair: Bernhard Moser

10:45	Elisa Perrone:
	Design of experiments for Copula Models, part 2
11:15	Francisco Serdio:
	Filtering the residual space

On Metric Equivalence for Event-Based Sampling

Bernhard Moser
SCCH, 3.07.2014

While Shannon's paradigm of sampling is based on equidistant points in time, triggered by a clock, level-crossing sampling schemes are based on the evaluation of the input signal's amplitude. Three types of level-crossing concepts are considered: (a) absolute level-crossings, (b) absolute level-crossings with hysteretic quantization, that ignores repeated crossings, and (c) thresholding changes. The latter is also referred to as send-on-delta. Such event-driven sampling principles are encountered in asynchronous event-based data acquisition of wireless sensor networks in order to reduce the amount of data transfer and energy consumption, in event-based imaging in order to realize high-dynamic range image acquisition or in biology in terms of neuronal spike trains.
The paper addresses the similarity between the event sequences which encode the quantized signals resulting from such event-based sampling concepts. It is shown that such event-driven sampling principles induce instability effects when using dissimilarity measures which are state-of-the-art in this context. As an alternative metric, Hermann Weyl's discrepancy norm is introduced. For this norm asymptotic metric equivalence can be shown which guarantees stability.

For details see

Moser, B. A. and Natschläger, T., On stability of distance measures for event sequences induced by level-crossing sampling, IEEE Trans. Signal Process. 62 (2014), no. 8, 1987—1999.

Improving Visual Discomfort Prediction of Stereoscopic Images by Disparity-Based Contrast

Werner Reisner, Bernhard Moser
SCCH, 3.07.2014

The problem of predicting the extent of visual discomfort, when watching stereoscopic images, is addressed. The phenomenon of visual discomfort depends on various influencing factors like the arrangement of the display system, the image quality and the design of 3D effects. Particularly, the computational efficiency of state-the-art prediction models is investigated. It turns out that a novel approach, based on the Haralick contrast feature applied on the disparity map, improves state-of-the-art computational models for predicting visual discomfort in terms of accuracy and, above all, time complexity. This result is underpinned by statistical evaluations based on public available assessment data.

The approach of this paper relies on the introduction of the Haralick contrast feature [1] (HC) in this context. It turns out that the HC feature allows a substantial improvement in this sense. In more detail, our experimental evaluations address the validation of the following two claims with respect to the features used in state-of-the-art approaches of [2,3]:

Claim 1 (Prediction Accuracy): The expected prediction accuracy,
which can be achieved by combinations of features including HC, is significantly higher than for combinations without HC.

Claim 2 (Time Complexity): HC allows substantial time complexity improvement without significant loss of prediction accuracy.

These claims are underpinned by statistically significant results on two public available databases [4], [5].

Remark: Paper recently submitted to IEEE Trans. on Broadcasting.

References:

[1] R. M. Haralick, K. Shanmugam, and I. H. Dinstein, “Textural features for image classification,” IEEE Trans. Systems, Man and Cybernetics, no. 6, 1973.

[2] D. Kim and K. Sohn, “Visual fatigue prediction for stereoscopic image,” IEEE Trans. Circuits and Systems for Video Technology, vol. 21, no. 2, pp. 231–236, 2011.

[3] M. Lambooij, W. A. IJsselsteijn, and I. Heynderickx, “Visual discomfort of 3D TV: assessment methods and modeling,” Displays, vol. 32, no. 4, pp. 209–218, 2011.

[4] Y. Jung, H. Sohn, S.-i. Lee, H. Park, and Y. Ro, Predicting visual discomfort of stereoscopic images using human attention model, 2013. [Online]. Available: http://ivylab.kaist.ac.kr/demo/3DVCA/3DVCA.htm.

[5] L. Goldmann, F. De Simone, and T. Ebrahimi, “Impact of acquisition distortions on the quality of stereoscopic images,” in Proc. Int. Workshop on Video Processing and Quality Metrics for Consumer Electronics-VPQM, 2010, pp. 1–6. Available: http://mmspg.epfl.ch/3diqa.

Design of experiments for Copula Models*

Elisa Perrone

Abstract In applications modeling dependencies by traditional covariance functions is often of limited use. Then stochastic dependence can easily and elegantly modeled by so-called copulas, functions with very special properties that have a strong connection with arbitrary marginal distributions (See[4]). The idea is to look into the relationship between the optimal design theory and the copula theory in order to find out what could be the best combination between the design model and the copula family. A first application of copulas to the optimal design theory was treated in [1]. In this work we give a general formulation for the application of copulas to the optimal design and we show a first example in order to give a more general view to what could be the strengths and the weakness of this approach.

Key words: Copulas, Optimal Experimental Design, Fisher Information Matrix.

1 Brief description

The collection of data requires a certain amount of effort such as time. A proper design potentially allows to make use of the resources in the most efficient way.

The classical optimal design problem is the estimation of the model parameters subject to the condition that a design criterion is optimized.

The choice of the design criterion will turn out to be a crucial part of an optimal design problem.

1.1 Introduction to the Optimal Design Theory

Let us consider a vector $\mathbf{x}^T = (x_1, \ldots, x_r) \in \mathscr{X}$ of control variables, where $\mathscr{X} \subset \mathbb{R}^r$ is a compact set.

The result of the observations is the vector:

Elisa Perrone
Institut für Angewandte Statistik, JKU - Linz, Austria. e-mail: elisa.perrone@jku.at

* PhD Thesis. Supervisor: Prof. W. G. Müller. Co-Supervisor: Prof. E. P. Klement.

$$\mathbf{y}(\mathbf{x}) = (y_1(\mathbf{x}),,\ldots,y_m(\mathbf{x})),$$

with

$$\mathbf{E}[\mathbf{Y}(x)] = \eta(\mathbf{x},\beta) = (\eta_1(\mathbf{x},\beta),\ldots,\eta_m(\mathbf{x},\beta)),$$

where $\beta = (\beta_1,\ldots,\beta_k)$ is a certain unknown parameter vector to be estimated and η_i are known functions.

In this work we will focus on the case $m = 2$.

Let us call $c_{\mathbf{Y}}(\mathbf{y}(\mathbf{x},\beta),\alpha)$ the joint probability density function of the random vector $\mathbf{Y}$, where $\alpha = (\alpha_1,\ldots,\alpha_l)$ are unknown parameters.

Definition 1. For a single observation the matrix $J(\mathbf{x},\beta,\alpha)$, a $(k+l)\times(k+l)$ matrix defined as follows

$$J(\mathbf{x},\beta,\alpha) = \begin{pmatrix} J_{\beta\beta}(\mathbf{x}) & J_{\beta\alpha}(\mathbf{x}) \\ J^T_{\beta\alpha}(\mathbf{x}) & J_{\alpha\alpha}(\mathbf{x}) \end{pmatrix} \tag{1}$$

where the matrix $J_{\beta\beta}(\mathbf{x})$ is the $(k\times k)$ matrix with the (i,j)th element defined as

$$\begin{aligned} &\mathbf{E}\left(-\frac{\partial^2}{\partial\beta_i\partial\beta_j}\log c_{\mathbf{Y}}(\mathbf{y}(\mathbf{x},\beta),\alpha)\right) = \\ &= \mathbf{E}\left(\left(\frac{\partial}{\partial\beta}\log c_{\mathbf{Y}}(\mathbf{y}(\mathbf{x},\beta),\alpha)\right)\left(\frac{\partial}{\partial\beta}\log c_{\mathbf{Y}}(\mathbf{y}(\mathbf{x},\beta),\alpha)\right)^T\right) \end{aligned} \tag{2}$$

and so are also the matrices $J_{\beta\alpha}(\mathbf{x})$ and $J_{\alpha\alpha}(\mathbf{x})$, is called the *Fisher Information Matrix*.

For r independent observations at $x_1,\ldots,x_r$, the corresponding Information matrix is

$$\mathbf{M}(\xi,\beta,\alpha) = \sum_{i=1}^{r} w_i J(x_i,\beta,\alpha)$$

where $\sum_{i=1}^{r} w_i = 1$ and

$$\xi = \begin{Bmatrix} \mathbf{x_1} & \mathbf{x_2} & \ldots & \mathbf{x_n} \\ w_1 & w_2 & \ldots & w_n \end{Bmatrix}.$$

Definition 2. A probability distribution function ξ on the actual design space Ξ , which is the class of all the probability distributions on the Borel set $\mathscr{X}$, is called a *design measure*.

The Information Matrix on a general design measure is:

$$M(\xi,\beta,\alpha) = E(J(\tilde{x},\beta,\alpha))$$

where $\tilde{x}$ is a random vector with distribution ξ.

The aim is to approximate theory is concerned with finding $\xi^*(\beta,\alpha)$ such that maximizes some function $\phi(M(\xi,\beta,\alpha))$.

We will consider as optimal criterion a function $\phi(M) = \log\det M$, if M is non singular. This criterion is called *D-optimality* and a design that maximize this function is called *D-optimal design*.

1.2 Copulas generalities

Definition 3. Let $\mathbb{I} = [0,1]$. A *two-dimensional copula* (or *2-copula*) is a bivariate function $C : \mathbb{I} \times \mathbb{I} \longrightarrow \mathbb{I}$ with the following properties:

1. for every u_1, $u_2 \in \mathbb{I}$
$$C(u_1,0) = 0,\ C(u_1,1) = u_1,\ C(0,u_2) = 0,\ C(1,u_2) = u_2; \tag{3}$$
2. for every u_1, u_2, u_3, $u_4 \in \mathbb{I}$ such that $u_1 \leq u_3$ and $u_2 \leq u_4$,
$$C(u_3,u_4) - C(u_3,u_2) - C(u_1,u_4) + C(u_1,u_2) \geq 0. \tag{4}$$

Theorem 1. ***Sklar's Theorem***
Let $\mathbf{F}_{Y_1Y_2}$ be a joint distribution function with marginals F_{Y_1} and F_{Y_2}. Then there exists a 2-copula C such that

$$\mathbf{F}_{Y_1Y_2}(y_1,y_2) = C(F_{Y_1}(y_1), F_{Y_2}(y_2)) \tag{5}$$

for all reals y_1, y_2.
If F_{Y_1} and F_{Y_2} are continuous, then C is unique; otherwise, C is uniquely defined on $Ran(F_{Y_1}) \times Ran(F_{Y_2})$.

Conversely, if C is a 2-copula and F_{Y_1} and F_{Y_2} are distribution functions, then the function $F_{Y_1Y_2}$ given by (5) is a joint distribution with marginals F_{Y_1} and F_{Y_2}.

1.3 The connection between Copulas and Optimal Designs

According to the Sklar's theorem, in the case $m = 2$, the joint probability density function written in Equation (2) is exactly the density of the copula function such that

$$F_{Y_1,Y_2}(y_1,y_2;\alpha) = \int c_{\mathbf{Y}}(\mathbf{y}(\mathbf{x},\beta),\alpha)d\mathbf{y} =$$
$$= C(F_{Y_1}(y_1), F_{Y_2}(y_2);\alpha).$$

The general idea of this work, hence, is to use a copula function as joint distribution function of the random vector $\mathbf{Y}$ and to investigate the dependence of the design with respect to the copula choice and to the copula parameter.

References

1. Denman N.G. , McGree J.M. , Eccleston J.A., Duffull S.B.:Design of experiments for bivariate binary responses modelled by Copula functions. Computational Statistics and Data Analysis (2011).
2. V. V. Fedorov. The design of experiments in the multiresponse case. Theory of Probability and its applications, vol XVI, (1971), Nr.2.
3. O. Krafft and M. Schaefer. D-Optimal Designs for a Multivariate Regression Model.Journal of Multivariate Analysis, vol 42, (1992), pag. 130-140.
4. Nelsen R.B. : An introduction to copulas. Springer-Verlag, New York, second edition, 2006.
5. S. D. Silvey: Optimal Design. CHAPMAN & HALL/CRC, 1980.

Filtering the residual space

Francisco Serdio[a], Ewdin Lughofer[a]

[a]*Department of Knowledge-Based Mathematical Systems, Johannes Kepler University Linz, Austria*

Abstract

Departing from a Fault Detection (FD) system [1] operating on the residual space, we introduce well-known filters from other domains to be applied to the residual signals generated by the FD models, with a double purpose: (i) to decrease the false positives of the systems and (ii) to increase the true positives of the system. Thus, the FD performance is increased by two means.

We have conducted experiments to demonstrate how, by using this simple technique, the residual signals are smoother due to a smaller standard deviation, but the underlying trend of the signal is still kept whereas the significant anomalies pointing to potential fault candidates are not filtered out. This is directly translated in a better residual-signal-tracking by means of a tolerance band, being less prone to false positives and more sensitive to true positives, i.e. to correct detections.

The research was performed with well-known existing filters, used in other domains, such as engineering, image processing, econometrics, etc. [2] [3].

Keywords: Fault detection, dynamic residual analysis, residual space, filters.

---

1. Filters

Moving average filters. They are effective filters to smooth data, and they have particular applications dealing with noisy pictures. They operate by replacing a point by an arithmetic mean of the values within an interval (neighborhood), and are formulated by

$$MAVG(x_i) = \frac{\sum_{k=0}^{N-1} x_{i-k}}{N}, \tag{1}$$

where MAVG stands for Moving AVeraGe and N is the size of the neighborhood to consider.

Modified moving average filters. The first element is computed as a normal moving average (1) whereas subsequent values are computed by

$$MMAVG(x_i) = MMAVG(x_{i-1}) + x_i - MAVG(x_{i-1}). \tag{2}$$

MMAVG stands for Modified Moving AVeraGe.

Email addresses: `francisco.serdio@jku.at` (Francisco Serdio), `ewdin.lughofer@jku.at` (Ewdin Lughofer)

Median average filters. They replace a neighborhood by its median value. They are widely used to deal with impulsive noise in images [4]. They are formulated by

$$MMED(x_i) = median\{x_{i-1}, ..., x_{i-N}\} , \quad (3)$$

where MMED stands for Moving MEDian and N is the size of the neighborhood to consider.

Gaussian filters. Described in the ISO 11562 standard [5], they have applications in electronics, signal processing and image processing [6]. A gaussian bell follows

$$GaussBell(x) = \frac{1}{\sigma \cdot \sqrt{2 \cdot \sigma}} \cdot e^{\left(-\frac{(x-c)^2}{2 \cdot \sigma^2}\right)} , \quad (4)$$

being c and σ the center and spread of the bell.

References

[1] F. Serdio, E. Lughofer, K. Pichler, T. Buchegger, and H. Efendic, "Residual-based fault detection using soft computing techniques for condition monitoring at rolling mills," *Information Sciences*, vol. 259, pp. 304–330, 2014.

[2] A. Antoniou, *Digital Filters: Analysis, Design, and Applications*. New York, NY: McGraw-Hill, 2000.

[3] R. Kapadia, *Digital Filters: Theory, Application and Design of Modern Filters*. New York: Wiley-VCH Verlag GmbH & Co. KGaA, 2012.

[4] A. M. Kizrak and F. Özen, "A new median filter based fingerprint recognition algorithm," *Procedia Computer Science*, vol. 3, pp. 859–865, 2011.

[5] I. 11562:1996, "Geometrical product specifications (gps) surface texture: profile method metrological characteristics of phase correct filters."

[6] D. Janecki, "Gaussian filters with profile extrapolation," *Precision Engineering*, vol. 35, pp. 602–606, 2011.