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Pattern Detection in Noisy Signals*

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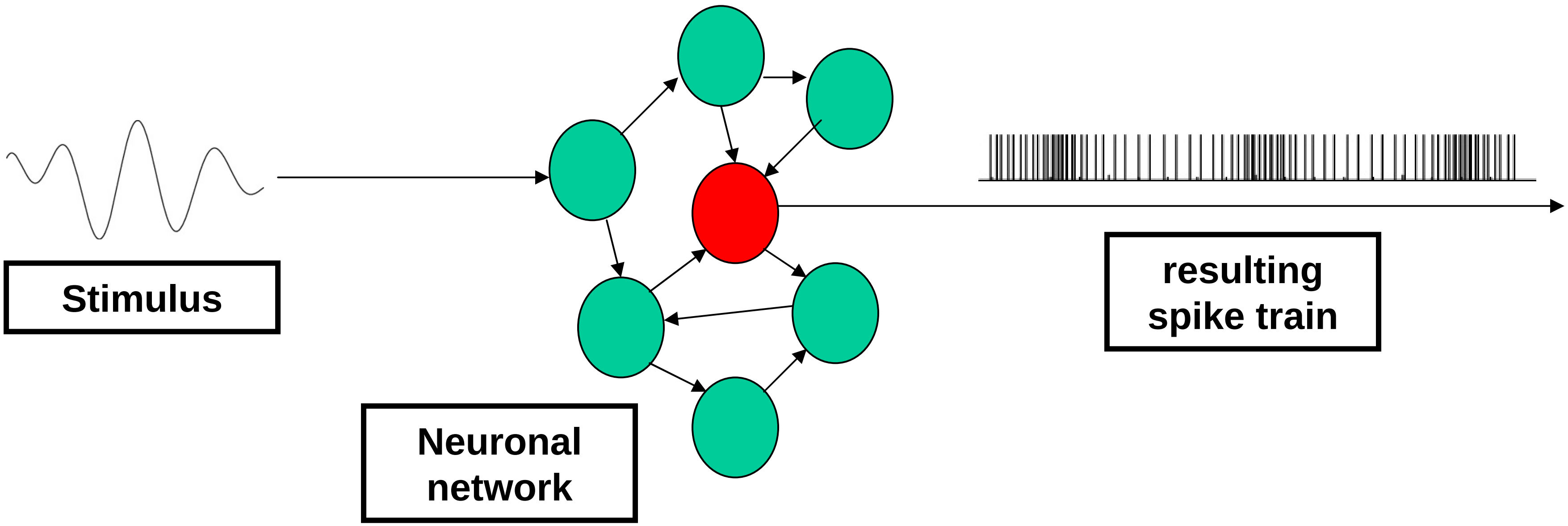
Overview

1. Patterns in single ISI series.
2. Problems of template-based pattern recognition.
3. Detecting patterns using the correlation integral.
4. The influence of noise and instability.
5. Estimation of the pattern length.
6. Application to neuronal data.

Patterns in single ISI series

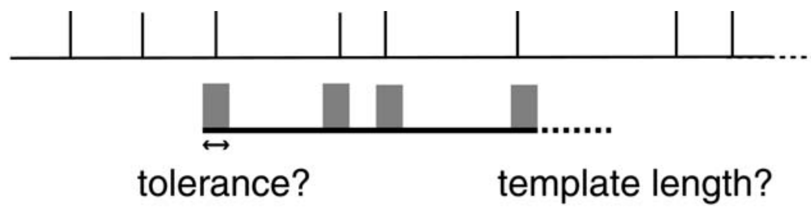


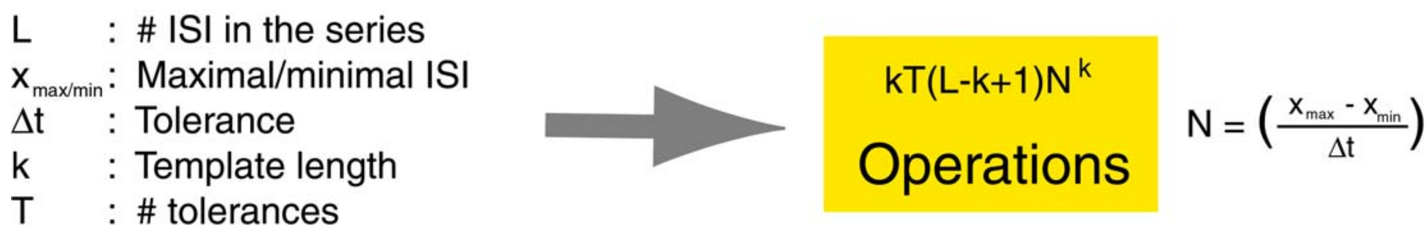
Spike patterns: Parts of the ISI series that repeat significantly more often than expected (e.g. assuming a Poisson process)

Their existence has been shown, their functional relevance is unclear.

Template-based pattern detection

The problem of noise: Due to various noise-sources in neuronal systems (thermal, synapse, network), spike patterns cannot be expected to repeat perfectly.



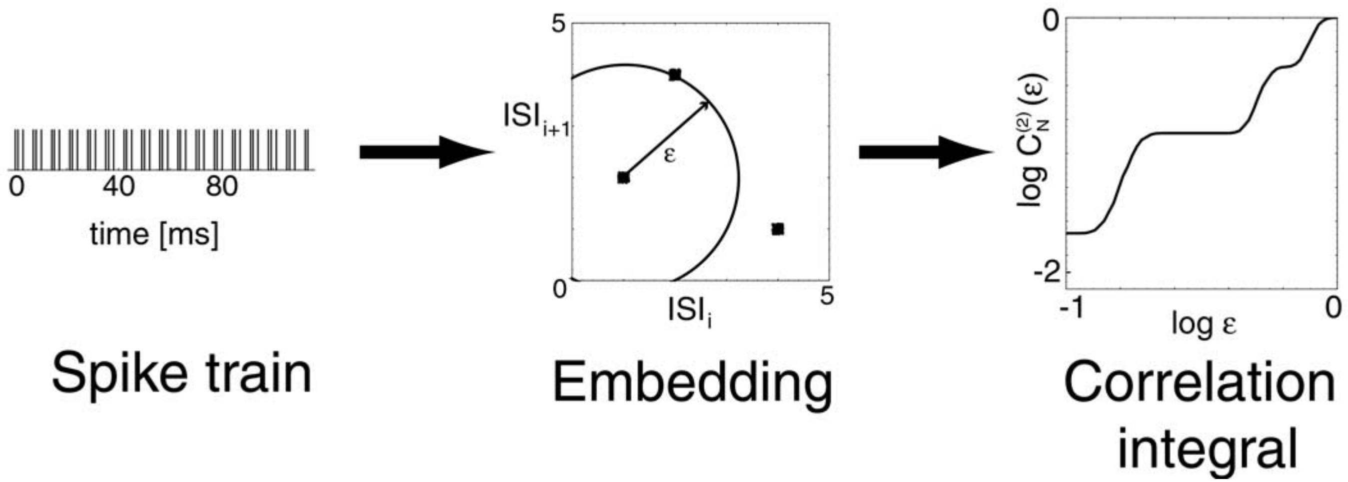


→ unbiased template approach only possible for small k

Patterns and the correlation integral

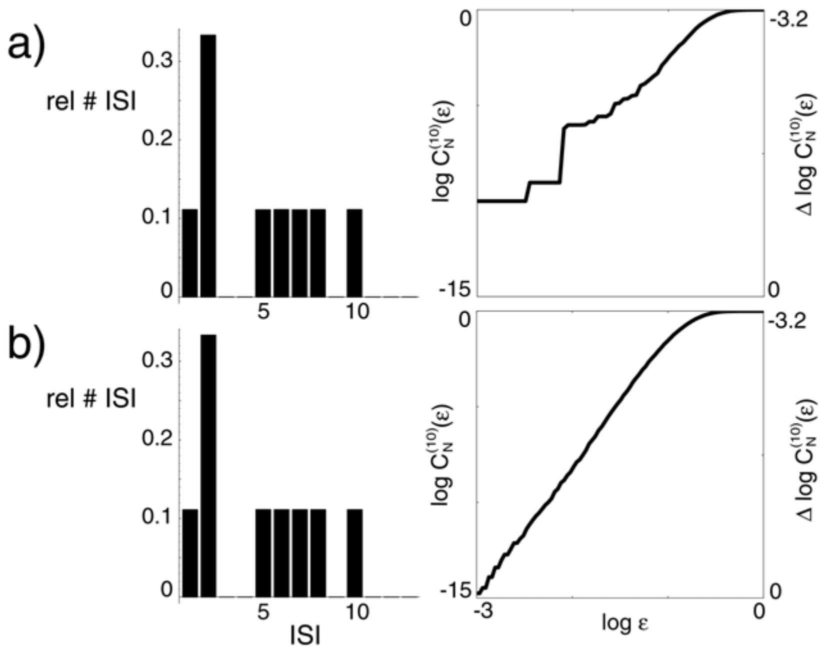
N:	# embedded points
m:	embedding dimension
ξ:	embedded point
θ():	Heavyside-function
|| ||:	Norm (e.g. max.)

$$C_N^{(m)}(\varepsilon) = \frac{1}{N(N-1)} \sum_{i \neq j} \theta(\varepsilon - || \xi_i^{(m)} - \xi_j^{(m)} ||)$$



Advantages: - The method is based on a standard, widely used procedure.
- Unbiased, purely statistical approach.
- Fast (~ kN^2 operations).

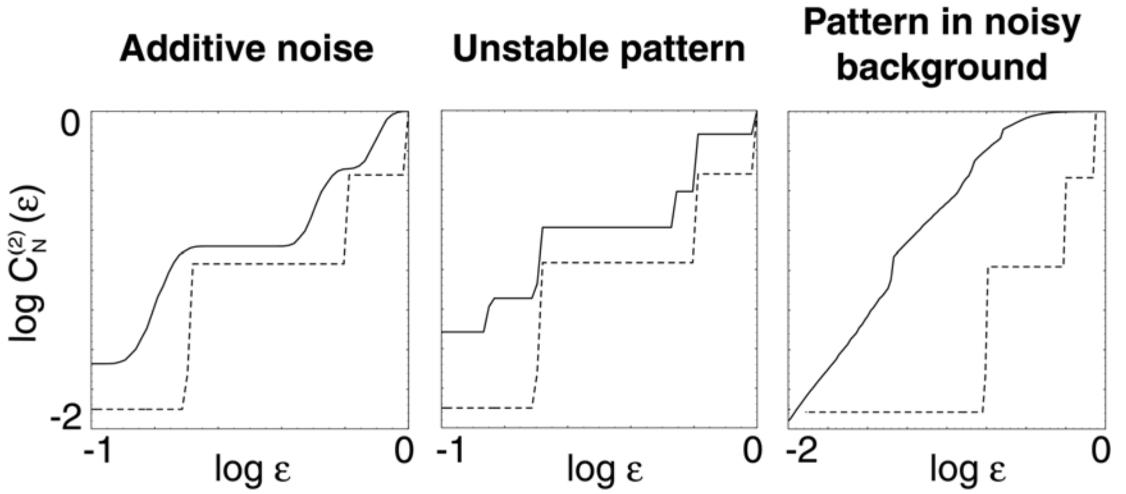
Patterned vs. random ISI series



Test 1: Compare two ISI series with identical distributions, but only series a) is composed of patterns.

Conclusion 1: Our method is able to distinguish series with patterns from series without patterns.

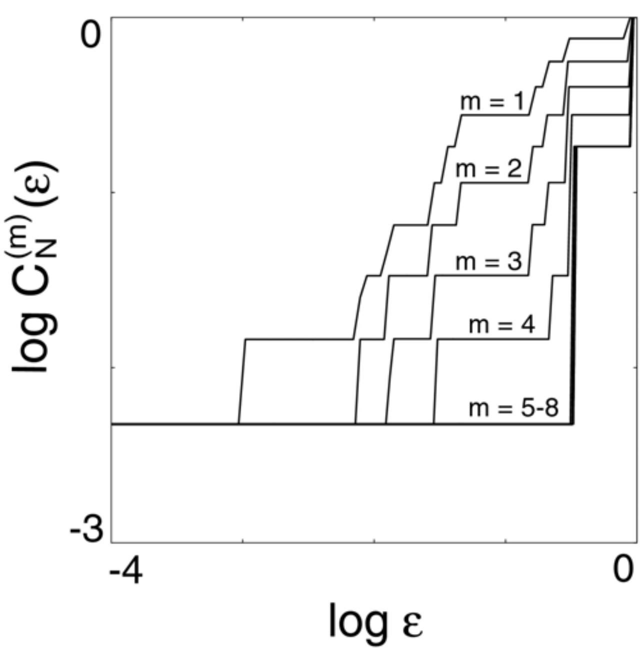
Blurred log-log steps



Test 2: Investigate three mechanisms affecting the log-log steps:
1) The pattern is affected by additive noise.
2) The pattern-generating process is unstable.
3) The pattern is embedded in a noisy background.

Conclusion 2: Our method is robust towards different influences of noise and instability.

Pattern length and step number: ideal case



m\n	1	2	3	4	5	6	7	8	9	10
1	0	1	3	6	10	15	21	28	36	45
2	0	1	2	4	8	12	18	24	32	40
3	0	1	1	3	6	9	15	20	28	35
4	0	1	1	2	4	7	12	16	24	30
5	0	1	1	2	2	5	9	13	20	25
6	0	1	1	2	2	3	6	10	16	21
7	0	1	1	2	2	3	3	7	12	17
8	0	1	1	2	2	3	3	4	8	13
9	0	1	1	2	2	3	3	4	4	9
10	0	1	1	2	2	3	3	4	4	5

$$n \quad \text{even:} \quad s(m,n) \leq \begin{cases} \frac{n(n-m)}{2} & : \quad 1 \leq m \leq \frac{n}{2} \\ \frac{n(n-m)+2m-n}{2} & : \quad \frac{n}{2} \leq m \leq n \\ \frac{n}{2} & : \quad m > n \end{cases} \tag{1}$$

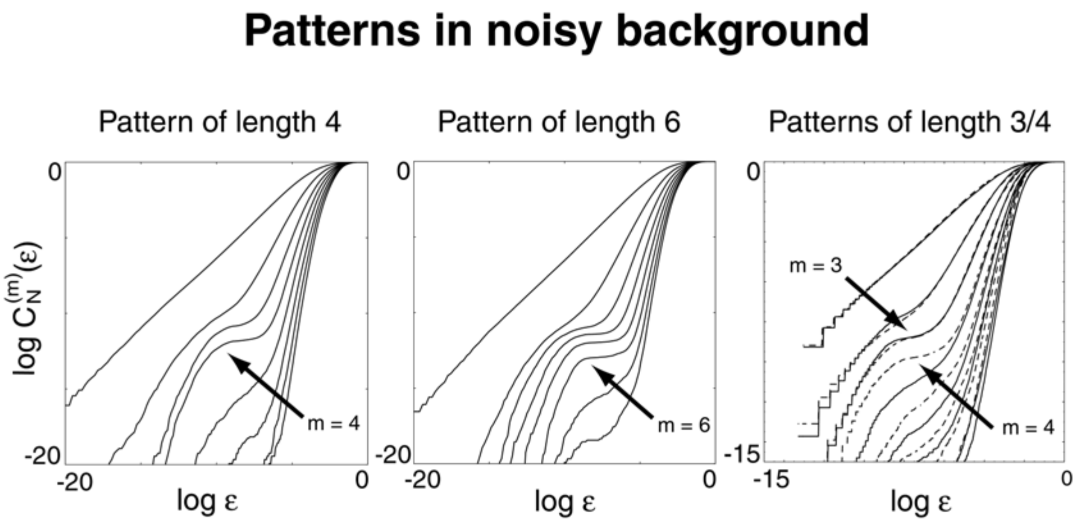
$$n \quad \text{odd:} \quad s(m,n) \leq \begin{cases} \frac{n(n-m)+m-1}{2} & : \quad 1 \leq m \leq n \\ \frac{n-1}{2} & : \quad m > n \end{cases} \tag{2}$$

A. Nikitchenko, M. Christen, R. Stoop, *in preparation*

Test 3: Investigate, if the number of steps can be related to the length *n* of a pattern (ideal case: ISI series generated by repeating a sequence, no noise).

Conclusion 3: An analytical solution is possible – but only in the ideal case.

Pattern length estimation



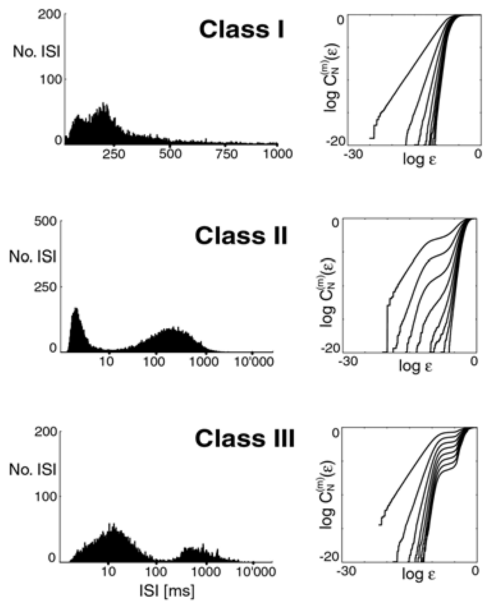
Test 4: Investigate, if the length *n* of a pattern embedded in a noisy background can be estimated using our method.

Conclusion 4: The most pronounced log-log step appears for $m = n$. Thus, pattern length estimation is possible.

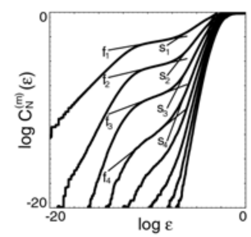
Application to neuronal data

# Files	
LGN	**V1**
4	6
12	6
1	5

Classification of (non)pattern firing

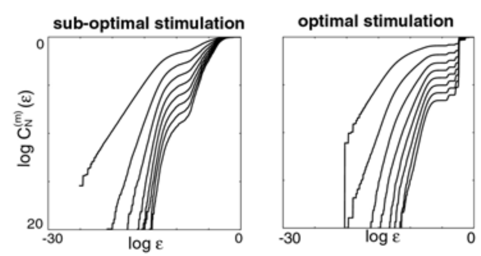


Pattern length



m	1	2	3	4
f/s	0.27	0.19	0.20	0.30

Pattern-sharpening



Results: 1) Our method leads to a classification of neurons (V1/LGN).
2) Class II: Short patterns of length 2 and 3.
3) „Pattern sharpening“ for optimal stimulus.

(PRE, 2004)

Conclusion

1. Steps in log-log plots of the correlation integral indicate the presence of patterns.
2. Pattern detection is
   - unbiased
   - simpe to implement
   - fast
   - noise-robust
3. Indicators for pattern length and the ISI forming the patterns (location of the steps) are provided, which e.g. support a succeeding template-based analysis.

Acknowledgement

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