Cluster marked cluster point processes

Ute Hahn



CENTRE FOR **STOCHASTIC GEOMETRY** AND ADVANCED **BIOIMAGING**

Aarhus University, Denmark

19th Workshop on Stochastic Geometry, Stereology and Image Analysis Luminy 15.05.2017



Positions of aquaporin molecules on kidney cell membrane



Lene N. Nejsum, Eva A. Christensen

Department of Molecular Biology and Genetics, AU, Denmark



Positions of aquaporin molecules on kidney cell membrane



Lene N. Nejsum, Eva A. Christensen

Department of Molecular Biology and Genetics, AU, Denmark



ca. $3300 \times 4100 \text{ nm}$

Aim: characterize clustering by pair correlation function









The pair correlation function is invariant to independent thinning of the process.



The pair correlation function is invariant to independent thinning of the process.



The pair correlation function is invariant to independent thinning of the process.





Aim: characterize clustering by pair correlation function





original pair correlation of \boldsymbol{X} : pcf(X)



5





Photo Activated Localization Microscopy



Published 2006, Method of the Year 2008, Nobel Prize in Chemistry 2014 (Betzig, Hell, Moerner)

Source: http://zeiss-campus.magnet.fsu.edu

Principle of Single-Molecule Localization Microscopy

Molecule positions estimated from digital images by maximum likelihood



Fitting Single-Molecule Pixel Data to a Gaussian Function

. igure e

Source: http://zeiss-campus.magnet.fsu.edu

Scientific hypothesis on PALM images:

- Points represent positions of fluorescent molecules,
- molecules fluoresce independently of each other.

Scientific hypothesis on PALM images:

- Points represent positions of fluorescent molecules,
- molecules fluoresce independently of each other.

Data:

- points registered in sequence of video frames,
- ▶ frame number available (range:[1400, 8000]).
- analyse as space-time or marked point pattern; inspect data in 3D, as points in $\mathbb{R}^2 \times$ frames.





PHE IN:

Drag mouse to rotate model. Use mouse wheel or middle button to zoom it.







EN 🗃 🔺 🎹 🖿 🗊 🔐

10:25 15-05-2017

6

Drag mouse to rotate model. Use mouse wheel or middle button to zoom it.









Ground process: cluster process X

- ► Parent process Y
- ► cluster template **C**₀
- ▶ independent clusters $C(y) \sim C_0 + y$, for all $y \in Y$
- superposition of clusters

$$\boldsymbol{X} = \bigcup_{\boldsymbol{y} \in \boldsymbol{Y}} \boldsymbol{C}(\boldsymbol{y}).$$



A Model for the data

Parent dependent marking

- ► Notation: m(u) mark of point u, mark space M.
- Location family of mark distributions for the clusters: {*M*_θ, θ ∈ Θ}.
- Parent process is i.i.d. marked, m(y) ~ T, with values in Θ.
- ▶ Points u ∈ C(y) are i.i.d. marked with m(u) ~ M_{m(y)}.

Resulting cluster marked cluster process (CMCpp) is mark stationary: Palm mark distribution

 $\mathcal{M}(d m) = \mathbf{E} \mathcal{M}_T(d m), \quad T \sim \mathcal{T},$

is independent of location.



Appropriate model for the data:

- Mark distributions \mathcal{M}_{θ} have small variance,
- distribution \mathcal{T} of location parameter spreads widely.

Points close to each other in space have preferentially similar frame marks.

Want: a statistics that shows that spatial clusters cover only a close range of marks (frames).

Stoyan's mark correlation function for stationary isotropic point process X: f measureable function on $\mathbb{M} \times \mathbb{M}$

$$k_f(r) := rac{\mathsf{E}[f(m(u),m(v)) \mid u,v \in \mathbf{X}]}{\mathsf{E}[f(M_1,M_2)]}, \ \|u-v\| = r, \ M_1,M_2 \sim \mathcal{M}, ext{indep}$$

- If **X** is independently marked, $k_f(r) \equiv 1$.
- For (quasi) continuous marks, the usual choice is $f(m_1, m_2) = m_1 m_2$.

- ► Under the model, |m(u) m(v)| is small for points from same cluster, but likely to be large for points from different clusters.
- Choose $f(m_1, m_2) = \mathbf{1}(|m_1 m_2| \in [t, t + \Delta])$, thus

$$k_f(r) = \frac{\Pr(|m(u) - m(v)| \in [t, t + \Delta] | u, v \in \boldsymbol{X}, ||u - v|| = r)}{\Pr(|m(u) - m(v)| \in [t, t + \Delta] | u, v \in \boldsymbol{X})}$$

- an odds ratio.



interpretation: close points (distance r < 200), are more likely to have similar frame numbers than different frame numbers.

Theorem.

Let:

X be a cluster marked cluster process with pair correlation function g_{X} ,

Y its parent process,

 $ilde{m{C}}$ the distribution of a random point in template clusters $m{C}$,

 $\mathcal{M}_{\theta}, \theta \in \Theta$ the mark distributions of the clusters,

 $\ensuremath{\mathcal{M}}$ the overall Palm mark distribution.

Let f be a function on \mathbb{M}^2 that fulfils, for independent M_1, M_2 :

$$\mathsf{E}f(M_1,M_2) \begin{cases} = 0, & M_1, M_2 \sim \mathcal{M}_{\theta}, \text{ for all } \theta \in \Theta, \\ > 0, & M_1, M_2 \sim \mathcal{M} \end{cases}$$

then for the mark correlation function k_f of \boldsymbol{X} ,

$$k_f(r)g_{\boldsymbol{X}}(r) = g_{\tilde{\boldsymbol{Y}}}(r),$$

where $\tilde{\pmb{Y}} = \tilde{\pmb{C}} * \pmb{Y}$ is the randomly $\tilde{\pmb{C}}$ -displaced parent process.

f-weighted second order factorial moment measure

$$\alpha_f^{(2)}(B_1, B_2) = \mathbf{E} \sum_{u, v \in \mathbf{X}}^{\neq} f(m(u), m(v)) \mathbf{1}_{B_1}(u) \mathbf{1}_{B_2}(v)$$

independent marking:

$$\alpha_f^{(2)}(B_1, B_2) = \underbrace{\mathsf{E}f(M_1, M_2)}_{=:\mu} \underbrace{\mathsf{E}\sum_{u, v \in \mathbf{X}}^{\neq} \mathbf{1}_{B_1}(u) \mathbf{1}_{B_2}(v)}_{=\alpha^{(2)}(B_1, B_2)}, \quad M_1, M_2 \sim \mathcal{M}, \text{indep.}$$

mark correlation function

$$k_f(\,,)$$
 is the density of $lpha_f^{(2)}$ wrt. $\mu lpha^{(2)}$.

independent locations (Poisson process)

$$lpha^{(2)}(B_1,B_2)=\Lambda(B_1)\Lambda(B_2)=:\Lambda^2(B1,B2)$$
 Λ : intensity measure

pair correlation function

g(,) is the density of $\alpha^{(2)}$ wrt. Λ^2

independent locations (Poisson process)

$$lpha^{(2)}(B_1,B_2)=\Lambda(B_1)\Lambda(B_2)=:\Lambda^2(B1,B2)$$
 Λ : intensity measure

pair correlation function

$$g(,)$$
 is the density of $\alpha^{(2)}$ wrt. Λ^2

thus, with k_f being the density of $\alpha_f^{(2)}$ wrt. $\mu \alpha^{(2)}$,

$$k_f \cdot g$$
 is the density of $\alpha_f^{(2)}$ wrt. $\mu \Lambda^2$.

$$\begin{aligned} \alpha_f^{(2)}(B_1, B_2) &= \mathbf{E} \sum_{u, v \in \mathbf{X}}^{\neq} f(m(u), m(v)) \mathbf{1}_{B_1}(u) \mathbf{1}_{B_2}(v) \\ &= \mathbf{E} \sum_{y \in \mathbf{Y}} \sum_{u, v \in \mathbf{C}(y)}^{\neq} f(m(u), m(v)) \mathbf{1}_{B_1}(u) \mathbf{1}_{B_2}(v) \\ &+ \mathbf{E} \sum_{y, y' \in \mathbf{Y}}^{\neq} \sum_{u \in \mathbf{C}(y)} \sum_{v \in \mathbf{C}(y')} f(m(u), m(v)) \mathbf{1}_{B_1}(u) \mathbf{1}_{B_2}(v) \end{aligned}$$

$$\alpha_{f}^{(2)}(B_{1}, B_{2}) = \mathbf{E} \sum_{u, v \in \mathbf{X}}^{\neq} f(m(u), m(v)) \mathbf{1}_{B_{1}}(u) \mathbf{1}_{B_{2}}(v)$$

= $\mathbf{E} \sum_{y \in \mathbf{Y}} \sum_{u, v \in \mathbf{C}(y)}^{\neq} \mathbf{E} f(m(u), m(v)) \mathbf{1}_{B_{1}}(u) \mathbf{1}_{B_{2}}(v)$
+ $\mathbf{E} \sum_{y, y' \in \mathbf{Y}}^{\neq} \sum_{u \in \mathbf{C}(y)} \sum_{v \in \mathbf{C}(y')} \mathbf{E} f(m(u), m(v)) \mathbf{1}_{B_{1}}(u) \mathbf{1}_{B_{2}}(v)$

$$\alpha_f^{(2)}(B_1, B_2) = \mathbf{E} \sum_{u, v \in \mathbf{X}}^{\neq} f(m(u), m(v)) \mathbf{1}_{B_1}(u) \mathbf{1}_{B_2}(v)$$
$$= \mathbf{E} \sum_{y \in \mathbf{Y}} \sum_{u, v \in \mathbf{C}(y)}^{\neq} \mu_{\mathbf{C}(y)} \mathbf{1}_{B_1}(u) \mathbf{1}_{B_2}(v)$$
$$+ \mathbf{E} \sum_{y, y' \in \mathbf{Y}}^{\neq} \sum_{u \in \mathbf{C}(y)} \sum_{v \in \mathbf{C}(y')} \mu \mathbf{1}_{B_1}(u) \mathbf{1}_{B_2}(v)$$

$$\alpha_f^{(2)}(B_1, B_2) = \mathbf{E} \sum_{u, v \in \mathbf{X}}^{\neq} f(m(u), m(v)) \mathbf{1}_{B_1}(u) \mathbf{1}_{B_2}(v)$$
$$= \mathbf{E} \sum_{y \in \mathbf{Y}} \sum_{u, v \in \mathbf{C}(y)}^{\neq} \mu_{\mathbf{C}(y)} \mathbf{1}_{B_1}(u) \mathbf{1}_{B_2}(v)$$
$$+ \mathbf{E} \sum_{y, y' \in \mathbf{Y}}^{\neq} \sum_{u \in \mathbf{C}(y)} \sum_{v \in \mathbf{C}(y')} \mu \mathbf{1}_{B_1}(u) \mathbf{1}_{B_2}(v)$$

with f such that $\mu_{\boldsymbol{C}(y)} = 0$,

$$= \mu \, \operatorname{\mathsf{E}}_{y,y' \in \operatorname{\mathsf{Y}}} \sum_{u \in \widetilde{\operatorname{\mathsf{C}}}} \sum_{v \in \widetilde{\operatorname{\mathsf{C}}}'} \mathbf{1}_{B_1}(y+u) \mathbf{1}_{B_2}(y'+v)$$

$$\begin{aligned} \alpha_f^{(2)}(B_1, B_2) &= \mathbf{E} \sum_{u, v \in \mathbf{X}}^{\neq} f(m(u), m(v)) \mathbf{1}_{B_1}(u) \mathbf{1}_{B_2}(v) \\ &= \mathbf{E} \sum_{y \in \mathbf{Y}} \sum_{u, v \in \mathbf{C}(y)}^{\neq} \mu_{\mathbf{C}(y)} \mathbf{1}_{B_1}(u) \mathbf{1}_{B_2}(v) \\ &+ \mathbf{E} \sum_{y, y' \in \mathbf{Y}}^{\neq} \sum_{u \in \mathbf{C}(y)} \sum_{v \in \mathbf{C}(y')} \mu \mathbf{1}_{B_1}(u) \mathbf{1}_{B_2}(v) \end{aligned}$$

with f such that $\mu_{\mathbf{C}(y)} = 0$,
 $&= \mu \ \nu^2 \mathbf{E} \sum_{y, y' \in \tilde{\mathbf{Y}}}^{\neq} \mathbf{1}_{B_1}(y) \mathbf{1}_{B_2}(y')$

 $\boldsymbol{\nu}:$ mean number of points in $\boldsymbol{\textit{C}}$

$$\alpha_{f}^{(2)}(B_{1}, B_{2}) = \mathbf{E} \sum_{u, v \in \mathbf{X}}^{\neq} f(m(u), m(v)) \mathbf{1}_{B_{1}}(u) \mathbf{1}_{B_{2}}(v)$$

= $\mathbf{E} \sum_{y \in \mathbf{Y}} \sum_{u, v \in \mathbf{C}(y)}^{\neq} \mu_{\mathbf{C}(y)} \mathbf{1}_{B_{1}}(u) \mathbf{1}_{B_{2}}(v)$
+ $\mathbf{E} \sum_{y, y' \in \mathbf{Y}}^{\neq} \sum_{u \in \mathbf{C}(y)} \sum_{v \in \mathbf{C}(y')} \mu \mathbf{1}_{B_{1}}(u) \mathbf{1}_{B_{2}}(v)$

with f such that $\mu_{\boldsymbol{C}(y)} = 0$,

$$= \mu \nu^{2} \mathbf{E} \sum_{y,y' \in \tilde{\mathbf{y}}}^{\neq} \mathbf{1}_{B_{1}}(y) \mathbf{1}_{B_{2}}(y')$$
$$= \mu \nu^{2} \alpha_{\tilde{\mathbf{y}}}^{(2)}(B_{1}, B_{2}).$$

pair correlation function g(r)mark correlation function $k_f(r)$ with $f(m_1, m_2) = |m_1 - m_2|$



pair correlation function g(r)mark correlation function $k_f(r)$ with $f(m_1, m_2) = |m_1 - m_2|$ $k_f(r)g(r)$



Model for ground process:

Matérn cluster process superimposed with Poisson "noise".



data

Model for ground process:

Matérn cluster process superimposed with Poisson "noise".



Jiaxin Chen



fittet model