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Feynman-Kac Interpretation Models

F. CEROU & P. DEL MORAL

IRISA-INRIA Rennes & Lab. J.A. Dieudonné, Univ. Nice Sophia Antipolis, France

- Brief introduction to Feynman-Kac and evolutionary particle models.
- Mean field particle interpretation models \simeq stochastic linearization Methods.
- Feynman-Kac interpretations of directed polymer measures
- Some asympt. analysis \oplus propagations of chaos expansions

Evolutionary type models

Simple Genetic Branching Algo.	<i>Mutation</i> <i>Selection/Branching</i>
Metropolis-Hastings Algo.	<i>Proposal</i> <i>Acceptance/Rejection</i>
Sequential Monte Carlo methods	<i>Sampling</i> <i>Resampling (SIR)</i>
Filtering/Smoothing	<i>Prediction</i> <i>Updating/Correction</i>
Particle ∈ Absorbing Medium	<i>Evolution</i> <i>Killing/Creation/Anhiling</i>

Other Botanical Names : multi-level splitting (Khan-Harris 51), prune enrichment (Rosenbluth 1955), switching algo. (Magill 65), matrix reconfiguration (Hetherington 84), restart (Villen-Altamirano 91), particle filters (Rigal-Salut-DM 92), SIR filters (Gordon-Salmon-Smith 93, Kitagawa 96), go-with-the-winner (Vazirani-Aldous 94), ensemble Kalman-filters (Evensen 1994), quantum Monte Carlo methods (Melik-Nightingale 1999), sequential Monte Carlo Methods (Arnaud Doucet 2001), spawning filters (Fisher-Maybeck 2002), SIR Pilot Exploration Resampling (Liu-Zhang 2002),...

\iff Particle Interpretations of Feynman-Kac models

Since R. Feynman's PhD. on path integrals 1942

Physics \longleftrightarrow Biology \longleftrightarrow Engineering Sciences \longleftrightarrow Probability/Statistics

– Physics :

- $FKS \in$ nonlinear integro-diff. eq. (\sim generalized Boltzmann models).
- Spectral analysis of Schrödinger operators and large matrices with nonnegative entries. (particle evolutions in disordered/absorbing media)
- Multiplicative Dirichlet problems with boundary conditions.
- Microscopic and macroscopic interacting particle interpretations.

– Biology :

- Self-avoiding walks, macromolecular polymerizations.
- Branching and genetic population models.
- Coalescent and Genealogical evolutions.

- **Rare events analysis :**
 - Multisplitting and branching particle models (Restart).
 - Importance sampling and twisted probability measures.
 - Genealogical tree based simulation methods.
- **Advanced Signal processing :**
 - Optimal filtering/smoothing/regulation, open loop optimal control.
 - Interacting Kalman-Bucy filters.
 - Stochastic and adaptative grid approximation-models
- **Statistics/Probability :**
 - Restricted Markov chains (w.r.t terminal values, visiting regions,...)
 - Analysis of Boltzmann-Gibbs type distributions (simulation, partition functions,...).
 - Random search evolutionary algorithms, interacting Metropolis/simulated annealing algo.
 - Bayesian methodology.

Mean field particle models=Non Linear Monte Carlo Methods

η_t Non linear PDE $\sim (L_{t,\eta})_{(t,\eta) \in (\mathbb{R}_+ \times \mathcal{P}(E))}$ infinitesimal generators

$$\frac{d}{dt} \eta_t(f) = \eta_t L_{t,\eta_t}(f) =_{\text{def.}} \int_E \eta_t(dx) L_{t,\eta_t}(f)(x)$$

\downarrow

Interacting Particle Approximation Model $\xi_t = (\xi_t^i)_{1 \leq i \leq N}$ infinitesimal generator \mathcal{L}_t

$$\mathcal{L}_t(F)(x^1, \dots, x^N) =_{\text{def.}} \sum_{i=1}^N L_{t,m(x)}^{(i)} F(x^1, \dots, x^i, \dots, x^N) \quad \text{with} \quad m(x) = \frac{1}{N} \sum_{i=1}^N \delta_{x^i}$$

$$\downarrow \quad (\eta_t^N := m(\xi_t))$$

$$d\eta_t^N(f) = \eta_t^N L_{t,\eta_t^N}(f) dt + dM_t^N(f) \quad \text{with} \quad \langle M^N(f) \rangle_t = \frac{1}{N} \int_0^t \eta_s^N \Gamma_{L_{s,\eta_s^N}}(f, f) ds$$

Example : (L. Miclo & P. DM SPA 2000)

$(X_t \simeq L_t - \text{motion on } E), (V_t : E \rightarrow \mathbb{R}_+) \rightsquigarrow \text{F.K. norm. model } \eta_t(f) := \gamma_t(f)/\gamma_t(1)$

$$\text{with } \gamma_t(f) = \mathbb{E} \left(f(X_t) \exp \left\{ - \int_0^t V_s(X_s) ds \right\} \right) \left(= \eta_t(f) \exp \left\{ - \int_0^t \eta_s(V_s) ds \right\} \right)$$

↓

$$\frac{d}{dt} \gamma_t(f) = \gamma_t(L_t^V(f)) \quad \text{with the Schrödinger operator} \quad L_t^V := L_t - V_t$$

$$\frac{d}{dt} \eta_t(f) = \eta_t L_{\eta_t}(f) := \int \eta_t(dx) \left\{ L_t(f)(x) + V_t(x) \int (f(y) - f(x)) \eta_t(dy) \right\}$$

Moran's type IPS Model $(\xi_t^i)_{1 \leq i \leq N} = \text{L-motions} \oplus \text{interacting jumps (V-intensity)}$

$$\begin{aligned} \mathcal{L}_t(F)(x^1, \dots, x^N) &= \sum_{i=1}^N L_t^{(i)} F(x^1, \dots, x^i, \dots, x^N) + \sum_{i=1}^N V_t(x^i) \\ &\quad \times \int (F(x^1, \dots, y^i, \dots, x^N) - F(x^1, \dots, x^i, \dots, x^N)) m(x)(dy^i) \end{aligned}$$

Particle approximation measures :

$$\eta_t^N(f) := \frac{1}{N} \sum_{i=1}^N f(\xi_t^i) \rightarrow_{N \rightarrow \infty} \eta_t(f)$$

$$\gamma_t^N(f) := \eta_t^N(f) \exp \left\{ - \int_0^t \eta_s^N(V) ds \right\} \rightarrow_{N \rightarrow \infty} \gamma_t(f) := \mathbb{E} \left(f(X_t) \exp \left\{ - \int_0^t V(X_s) ds \right\} \right)$$

Propagation of chaos property :

$$\text{Law}(\xi_t^1, \dots, \xi_t^q) \rightarrow_{N \rightarrow \infty} \eta_t^{\otimes q}$$

Discrete generation models

$$\eta_n = \eta_{n-1} K_{n,\eta_{n-1}} =_{\text{def.}} \int_{E_{n-1}} \eta_{n-1}(dx) \underbrace{K_{n,\eta_{n-1}}(x, \cdot)}_{\text{Markov transitions}}$$

↓

Interacting Particle Approximation Model

$$\forall 1 \leq i \leq N \quad \xi_{n-1}^i \longrightarrow \xi_n^i \sim K_{n,\eta_{n-1}^N}(\xi_{n-1}^i, \cdot) \quad \text{with} \quad \eta_{n-1}^N = \frac{1}{N} \sum_{i=1}^N \delta_{\xi_{n-1}^i}$$

↓

$$\eta_n^N = \eta_{n-1}^N K_{n,\eta_{n-1}^N} + \frac{1}{\sqrt{N}} W_n^N \quad \text{with} \quad W_n^N \simeq \text{centered Gauss field}$$

↔ adaptive dynamics, genetic and branching population model, etc.

Example : Feynman-Kac & Genetic interpretation models

(Discrete time parameter $n \in \mathbb{N} = \{0, 1, 2, \dots\}$, state spaces E_n ($\in \{\mathbb{Z}^d, \mathbb{R}^d, \underbrace{\mathbb{R}^d \times \dots \times \mathbb{R}^d}_{(n+1)-\text{times}}\}$))

- *Reference Markov chain/Mutation/exploration/prediction/proposal :*
 - Markov transitions $M_n(x_{n-1}, dx_n)$ from E_{n-1} into E_n .
- *Environment/Selection/absorption/updating/acceptance :*
 - Potential functions G_n from E_n into $[0, 1]$.

Random environment/medium impurities :

↪ $(G_n(x_n))_{n,x_n}$ independent r.v. (Ex. : X_n r.w. $\in \mathbb{Z} \oplus \text{Bernoulli} \in \{1, e^{-\beta}\}$)

Feynman-Kac models → **weighted random paths** → **directed polymers**

Directed Polymer measure :

$$d\mathbb{Q}_n = \frac{1}{Z_n} \left\{ \prod_{0 \leq p < n} G_p(X_p) \right\} d\mathbb{P}_n \quad \text{with} \quad \mathbb{P}_n = \text{Law}(X_0, \dots, X_n)$$

- $0 = G_n(x_n) \iff$ hard obstacle
- $0 < G_n(x_n) < 1 \iff$ repulsive point/soft obstacle
- $G_n(x_n) \geq 1 \iff$ attractive point

n-th marginals :

$$\eta_n(f_n) = \gamma_n(f_n)/\gamma_n(1) \quad \text{with} \quad \gamma_n(f_n) := \mathbb{E} \left(f_n(X_n) \prod_{0 \leq p < n} G_p(X_p) \right) \quad (Z_n = \gamma_n(1))$$

Path models, Markov monomial $X'_n \in E'_n$:

[$X_n = (X'_0, \dots, X'_n)$ and $G_n(X_n) = G'_n(X'_n)$] ↪ Same Math. Model !!

Examples :

- *Self avoiding walks* $X'_n \in \mathbb{Z}^d$

$$X_n = (X'_0, \dots, X'_n) \quad \text{and} \quad G_n(X_n) = 1_{\notin \{X'_0, \dots, X'_{n-1}\}}(X'_n)$$

FK model :

$$\gamma_n(1) = \text{Proba}(\forall 0 \leq p \neq q \leq n, \quad X'_p \neq X'_q)$$

and

$$\eta_n = \text{Law}(X'_0, \dots, X'_n \mid \forall 0 \leq p \neq q \leq n, \quad X'_p \neq X'_q)$$

Ex. : (*Connectivity constants*)

$$\gamma_n(1) = \frac{1}{(2d)^n} \times \#\{\text{non intersecting walks with length } n\} \simeq \frac{\exp(c n)}{(2d)^n}$$

- *Edwards' model*

$$X_n = (X'_0, \dots, X'_n) \quad \text{and} \quad G_n(X_n) = \exp \left\{ -\beta \sum_{0 \leq p < n} 1_{X'_p}(X'_n) \right\}$$

- Random medium $(G_n(x))_{n,x}$ i.i.d random variables

$$G_n(x) \in \{0, 1\} \Rightarrow \eta_n = \text{Law}(X_n \mid X \in \text{percolation clusters})$$

- Weak-Strong disorder : $(\mathbb{E}(G_n(x)) = 1)$ (Subadditivity \oplus concentration)

$$W_n := \frac{1}{n} \log Z_n = \frac{1}{n} \log \gamma_n(1) = \frac{1}{n} \sum_{0 \leq p < n} \log \eta_p(G_p) \xrightarrow{n \rightarrow \infty} W_\infty = \begin{cases} 0 & \text{Strong disorder} \\ < 0 & \text{Weak disorder} \end{cases}$$

Random Walk $\in \mathbb{Z}^d$, $G_n = e^{-\beta V_n}$ regular medium :

- strong disorder ($d = 1, 2$) ; weak disorder ($d \geq 3$, small β)
[Ref. : Bolthausen, Carmona-Hu, Comets-Yoshida-Shiga, Imbrie-Spencer]
- $d \geq 3$ and small $\beta \Rightarrow$ Diffusive regime [Comets, Bolthausen, Sinai]
- Strong disorder \iff Replica localisation [Comets, Derrida, Spohn, Vargas]
- Conjectures : (Under \mathbb{Q}_n) [Universal constants, small β]

$$|X_n| \simeq n^{a(d)} \quad \text{and} \quad \log \gamma_n(1) - \mathbb{E}(\gamma_n(1)) \simeq n^{b(d)} \quad (b(d) \leq 1/2)$$

$$(a(1), b(1)) = (2/3, 1/3) \quad \text{and} \quad b(d) = 2a(d) - 1$$

[Comets, large deviations arguments] $b(d) \geq 2a(d) - 1 (\Rightarrow a(d) \leq 3/4)$

Feynman-Kac and Particle Interpretation Models

I-Nonlinear equation ($G_n \leq 1$)

$$\eta_{n+1} = \eta_n K_{n+1, \eta_n}$$

with the composition transition

$$K_{n+1, \eta_n} = S_{n, \eta_n} M_{n+1}$$

the selection type Markov transition

$$S_{n, \eta}(x, dy) = G_n(x) \delta_x(dy) + (1 - G_n(x)) \Psi_n(\eta)(dy)$$

and the Boltzman transformation

$$\Psi_n(\eta)(dy) = \frac{1}{\eta(G_n)} G_n(y) \eta(dy)$$

II-Particle interpretation=Genetic Model \Rightarrow Markov $\xi_n = (\xi_n^1, \dots, \xi_n^N) \in E_n^N = E_n \times \dots \times E_n$

$$\xi_n \in E_n^N \xrightarrow{\text{selection}} \widehat{\xi}_n \in E_n^N \xrightarrow{\text{mutation}} \xi_{n+1} \in E_{n+1}^N$$

- **Selection transition** ($\exists \neq$ types \rightarrow Ex. : accept/reject)

$$\xi_n^i \rightsquigarrow \widehat{\xi}_n^i = \xi_n^i \quad \text{with proba. } G_n(\xi_n^i) \quad \text{[Acceptance]}$$

Otherwise we select a better fitted individual in the current configuration

$$\widehat{\xi}_n^i = \xi_n^j \quad \text{with proba. } G_n(\xi_n^j) / \sum_{k=1}^N G_n(\xi_n^k) \quad \text{[Rejection + Selection]}$$

- **Mutation transition**

$$\widehat{\xi}_n^i \rightsquigarrow \xi_{n+1}^i \sim M_{n+1}(\widehat{\xi}_n^i, \bullet)$$

Genetic Evolution Model on Path Spaces=Genealogical tree model

Occupation/Empirical measures ($\forall f_n$ test function on E_n)

$$\eta_n^N(f_n) = \frac{1}{N} \sum_{i=1}^N f_n(\xi_n^i) = \frac{1}{N} \sum_{i=1}^N f_n \underbrace{(\xi_{0,n}^i, \xi_{1,n}^i, \dots, \xi_{n,n}^i)}_{i\text{-th ancestral lines}} \xrightarrow{N \rightarrow \infty} \eta_n(f_n)$$

Unbias-particle measures & Unnormalized Feynman-Kac measures :

$$\gamma_n^N(f_n) = \eta_n^N(f_n) \times \prod_{0 \leq p < n} \eta_p^N(G_p) \xrightarrow{N \rightarrow \infty} \gamma_n(f_n) = \eta_n(f_n) \times \prod_{0 \leq p < n} \eta_p(G_p)$$

Asymptotic theory $(n, N) \rightarrow \infty$ (usual LLN, CLT, LDP,...)

Example : [$p \geq 1 + \mathcal{F}_n$ not too large + regular mutations]

(JTP 2000, joint work with M. Ledoux+ FK Formulae Springer 2004)

$$\sup_{n \geq 0} \mathbb{E} \left(\sup_{f_n \in \mathcal{F}_n} |\eta_n^N(f_n) - \eta_n(f_n)|^p \right)^{1/p} \leq c(p)/\sqrt{N}$$

and

$$\sup_{n \geq 0} \mathbb{P}(|\eta_n^N(f_n) - \eta_n(f_n)| > \epsilon) \leq (1 + \epsilon \sqrt{N/2}) \exp - \frac{N\epsilon^2}{\sigma^2}$$

Functional representation at any order : $(\mathbb{Q}_{n,q}^N(F) := \mathbb{E}((\gamma_n^N)^{\otimes q}(F)))$

↪ Coalescent tree based functional representations for some Feynman-Kac particle models.

(joint work with F. Patras and S. Rubenthaler)

thm :

$$\mathbb{Q}_{n,q}^N = \gamma_n^{\otimes q} + \sum_{1 \leq k \leq (q-1)(n+1)} \frac{1}{N^k} \partial^k \mathbb{Q}_{n,q}$$

and

$$\mathbb{P}_{n,q}^N \simeq \eta_n^{\otimes q} + \sum_{1l \leq l \leq k} \frac{1}{N^l} \partial^l \mathbb{P}_{n,q} + \frac{1}{N^{k+1}} \partial^{k+1} \mathbb{P}_{n,q}^N \quad \text{with} \quad \sup_{N \geq 1} \|\partial^{k+1} \mathbb{P}_{n,q}^N\|_{\text{tv}} < \infty$$

Consequences : Sharp + strong propagations of chaos estimates at any order, Wick product formulae on forests, sharp \mathbb{L}_p -mean error bounds, law of large numbers for U -statistics for interacting processes,

Rare events : Adaptive Algorithm

Parameters

N the number of particles.

K the number of succeeding particles at each step.

Initialization

Draw an i.i.d. N -sample $\xi_j, j = 1, \dots, N$ of the trajectory of X until stopping time T_j^0 when it hits A_0 , compute $S_j = \sup_{0 \leq t \leq T_j^0} \Phi(\xi_j(t))$.

Sort the $S_j, j = 1, \dots, N$ in decreasing order, and reorder the ξ_j, T_j^0 accordingly.

Take S_K , the K^{th} sorted value, and for $j = 1, \dots, K$ compute $T_j^S = \inf\{0 \leq t \leq T_j^0, \Phi(\xi_j(t)) \geq S_K\}$.
 $m \leftarrow 0$.

Iterations

while $S_K < \lambda_R$ do

$m \leftarrow m + 1$.

 for $j = K + 1, \dots, N$

 Choose at random an index ℓ in $1, \dots, K$ with uniform probability.

 Let $\xi_j = \xi_\ell$ until time T_ℓ^S , and extend the trajectory by simulation until new T_j^0 when it hits A_0 ,
 re-compute $S_j = \sup_{0 \leq t \leq T_j^0} \Phi(\xi_j(t))$.

 endfor

 Sort the $S_j, j = 1, \dots, N$ in decreasing order, and reorder the ξ_j, T_j^0 accordingly.

 Take S_K , the K^{th} sorted value, and for $j = 1, \dots, K$ re-compute $T_j^S = \inf\{0 \leq t \leq T_j^0, \Phi(\xi_j(t)) \geq S_K\}$.

endwhile

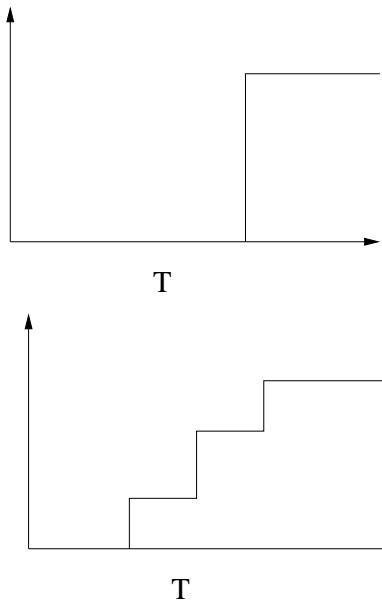
let \tilde{P} be the proportion of trajectories that actually hit R .

Output

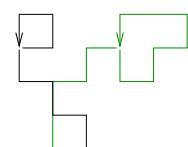
estimate the probability of the rare event by $\hat{P}_2 = \tilde{P} \cdot (\frac{K}{N})^m$.



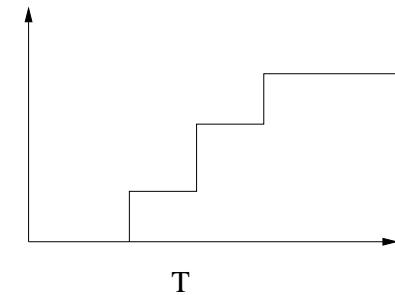
Cumulative distrib.



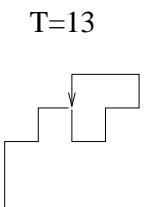
$T=10$



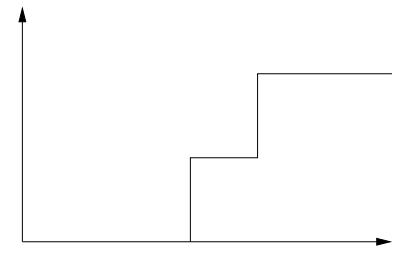
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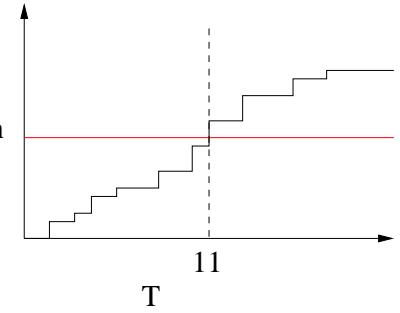
$T=13$



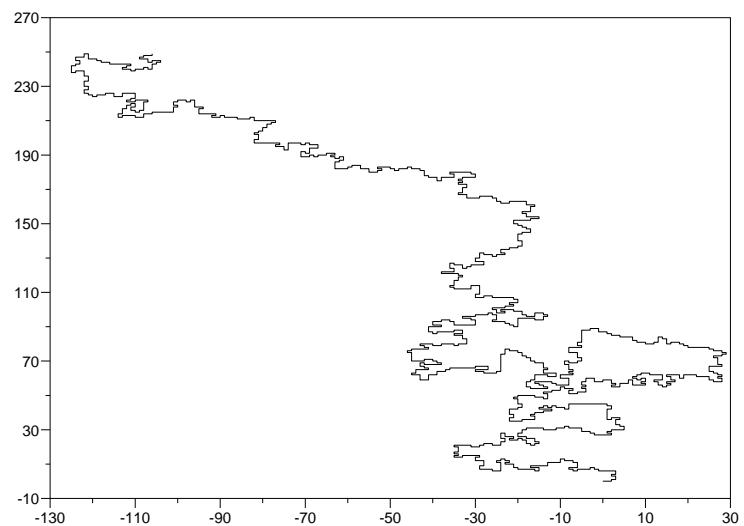
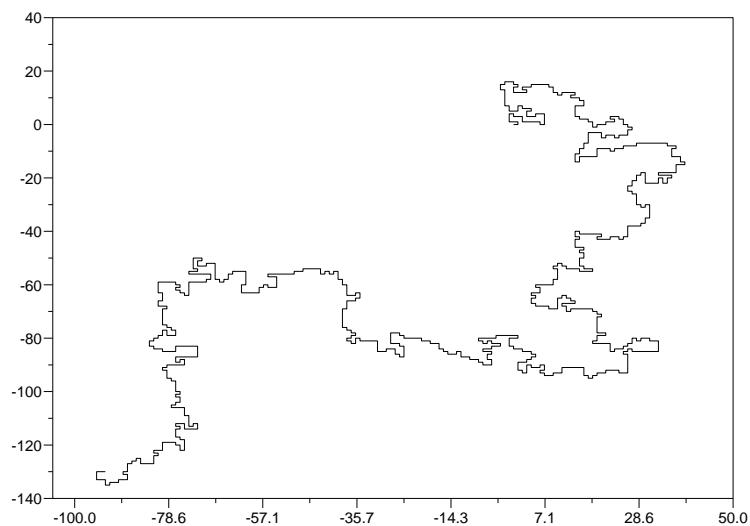
Cumulative distrib.



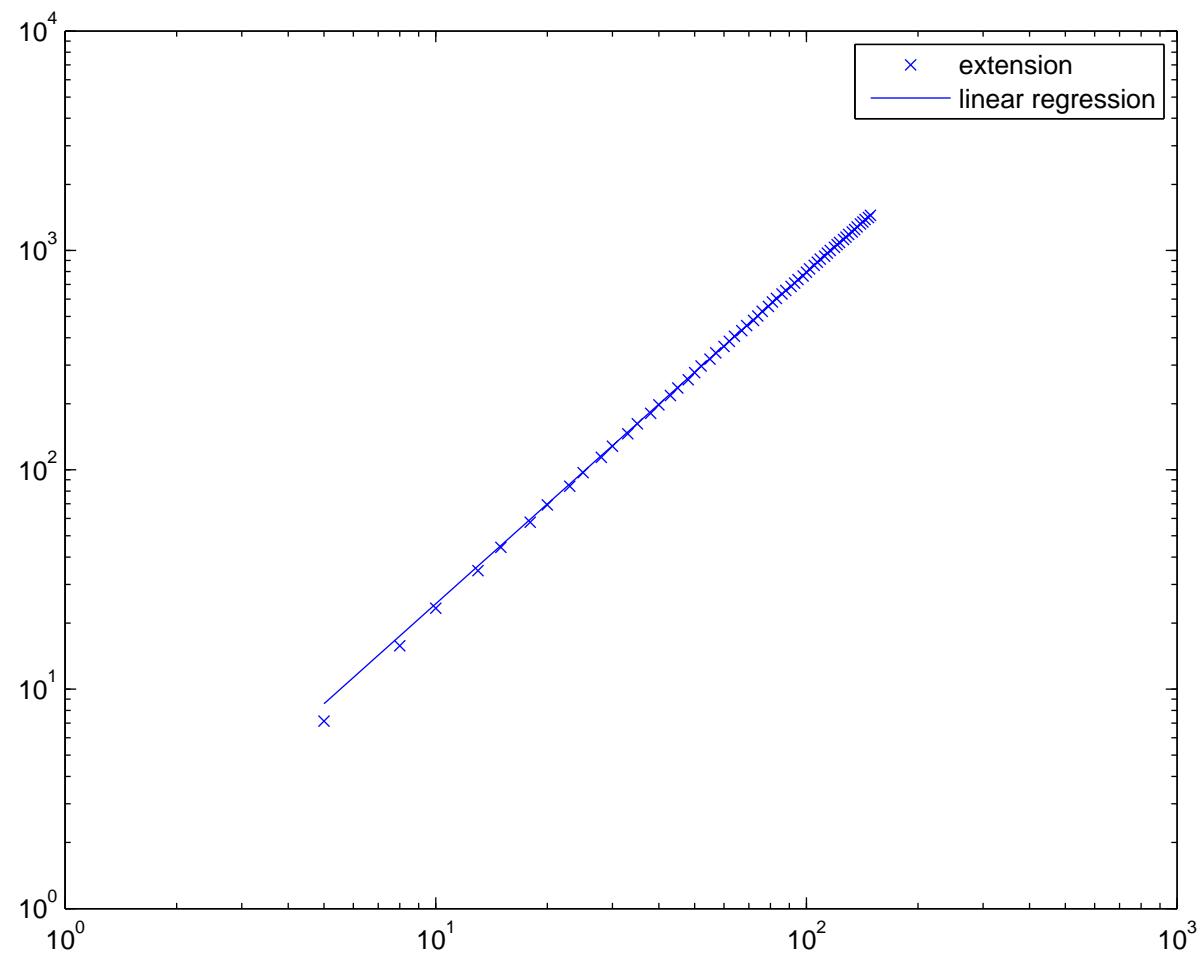
Cumulative distrib.



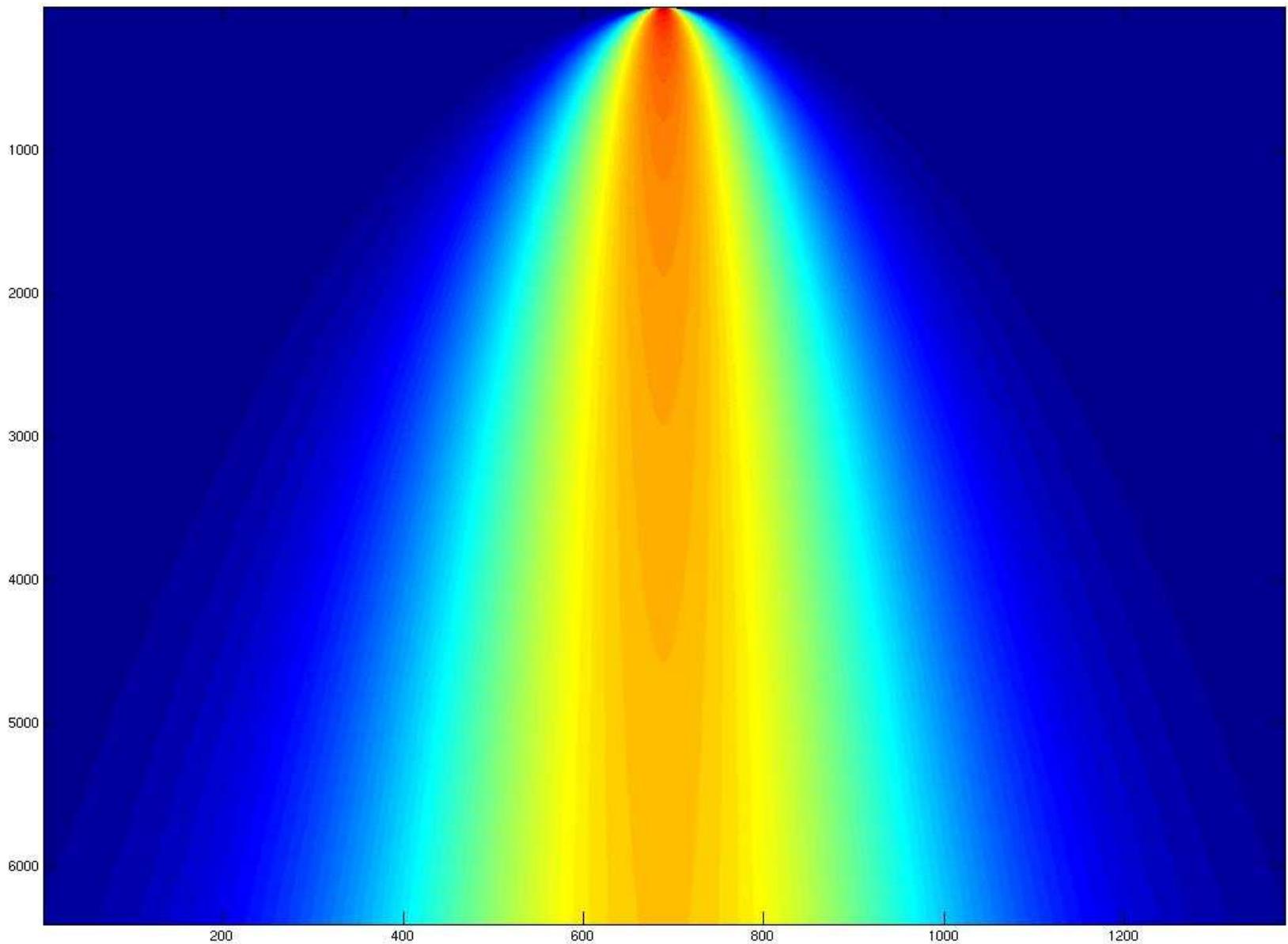
Adaptive algorithm applied to self avoiding walks on the 2 dimensional lattice.



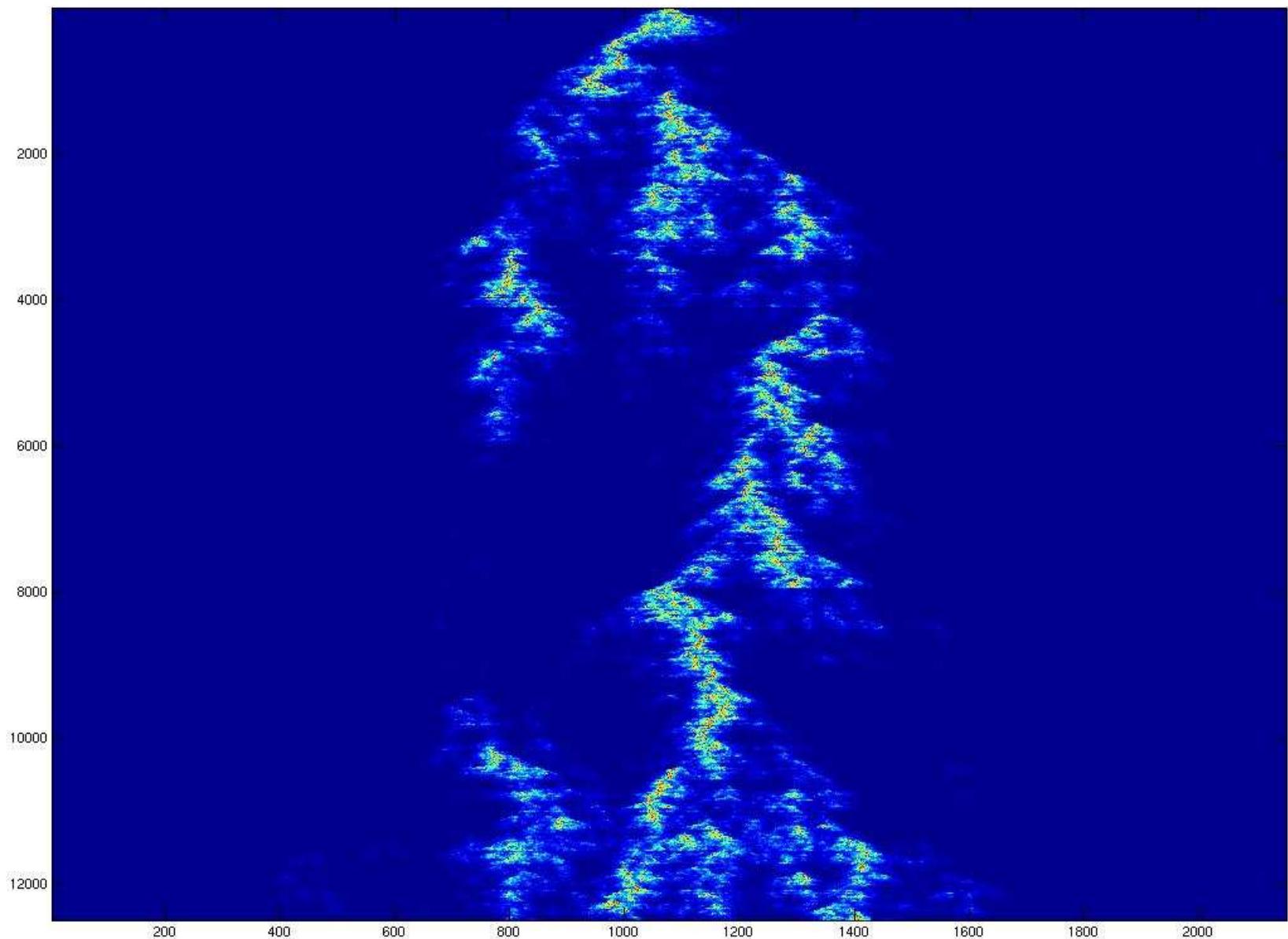
Examples of **saw**.



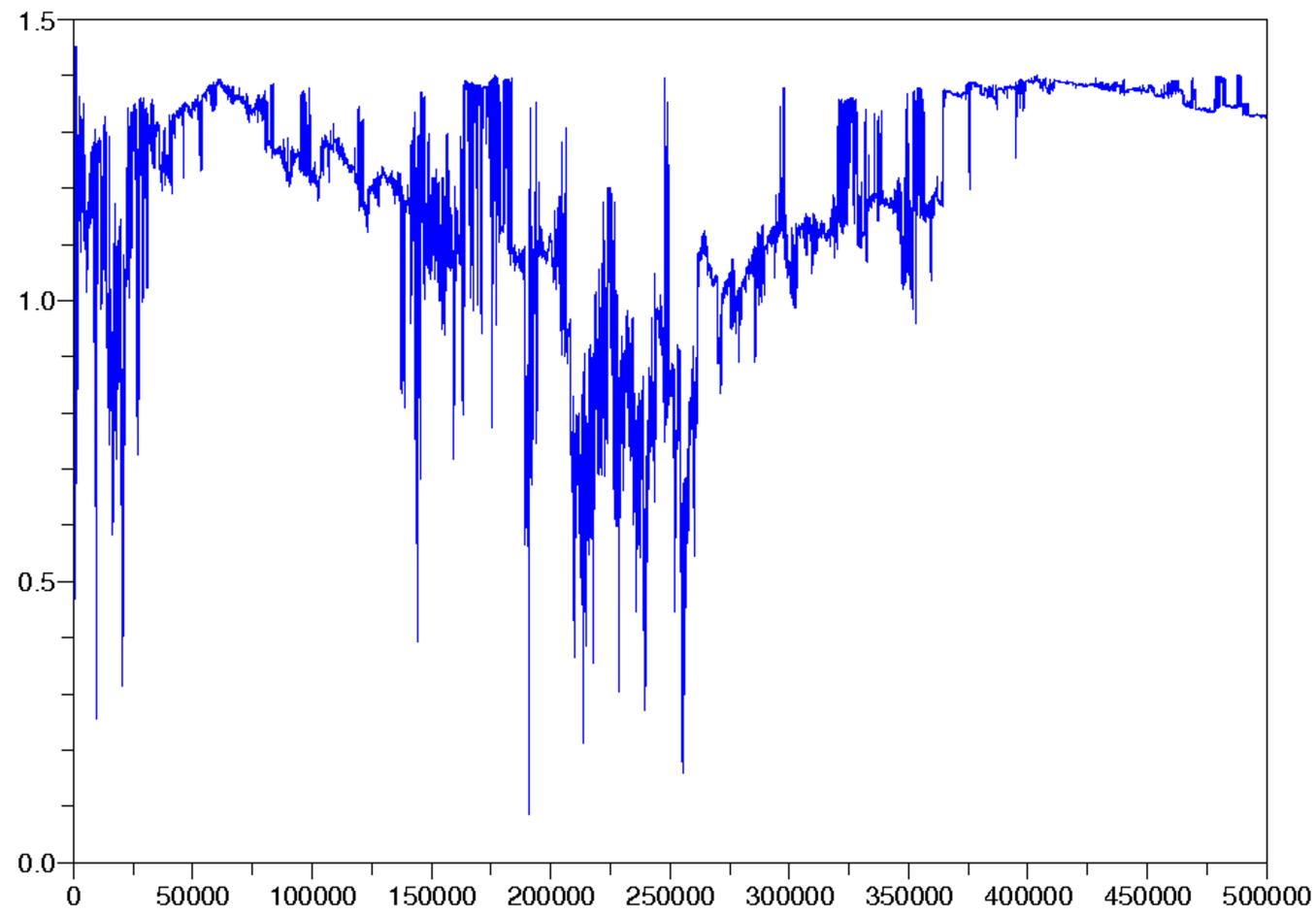
Extension exponent $\gamma \simeq 1.511$ (conjecture : 1.5).



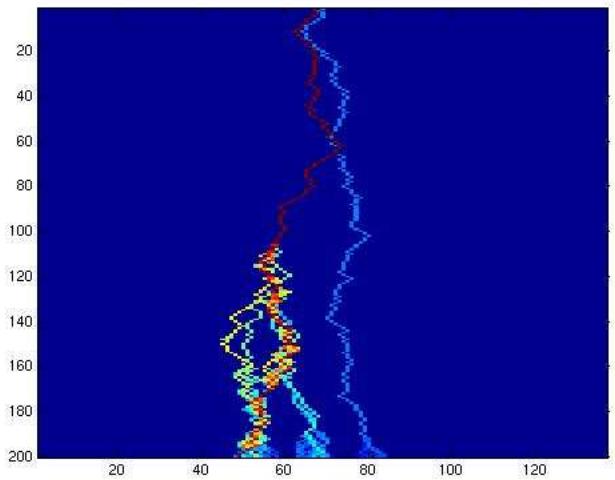
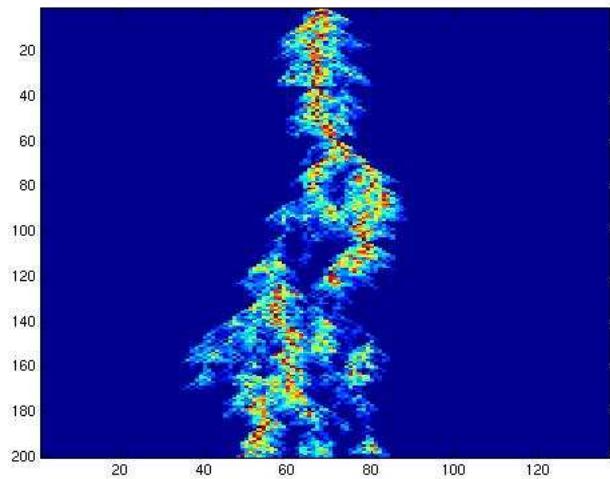
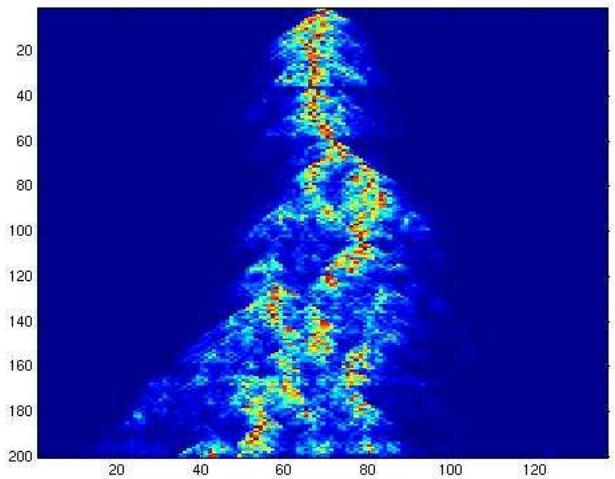
Standard random walk



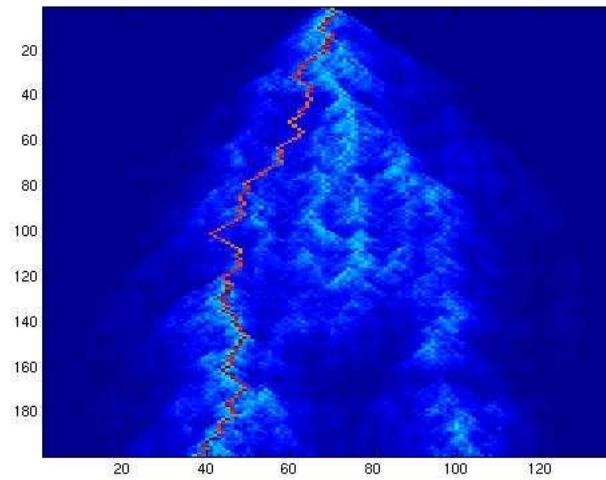
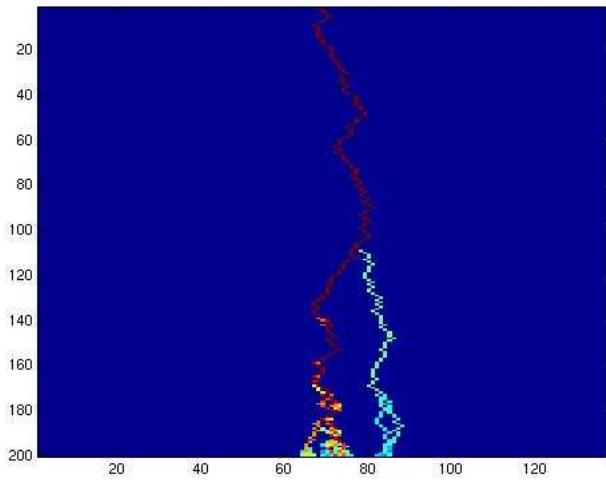
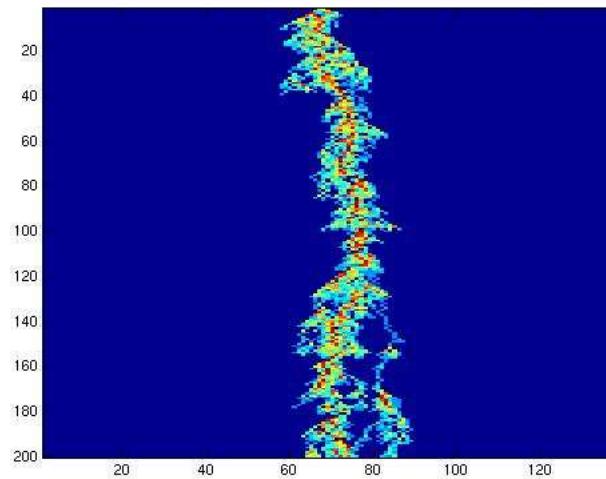
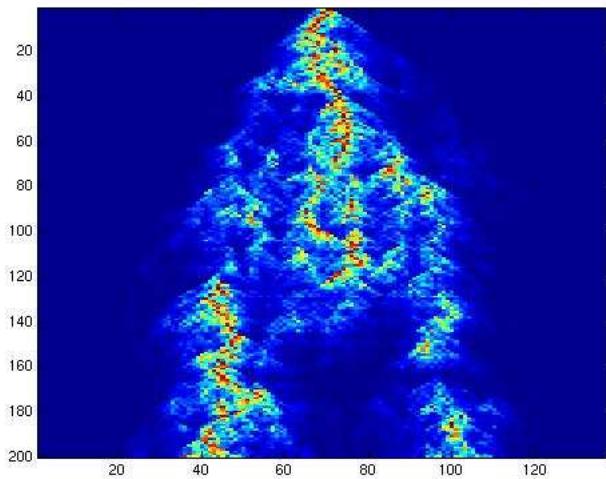
Random walk in strongly disordered medium.



Strongly disordered medium, $\log E(X_t^2)/\log t$ (conjecture : 4/3).



5000 particles, the law is well approximated.



1000 particles, the particles cannot track the path with maximum likelihood.