GNSS Urban Localization Enhencement using Dirichlet Process Mixture Modelling

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Abstract

Precise GNSS localization in urban environment is a key point for the development of a new generation of applications based on systems like GPS or Galileo. Whatever the complexity of the systems, measurement noise linked to multipath cannot be taken into account a priori and must be processed locally. We have shown that this noise can be modelled by a mixture of gaussian. Classical receiver based on least squares estimation or Extended kalman Filter are therefore not designed to account for such a type of error. A mixture modelling must then be considered along with a new generation of estimation algorithm. It is however difficult to estimate a priori the right mixture component number. Dirichlet Process Mixture (DPM) is thus a interesting way to manage this problem. We show in this paper that DPM modelling along with bayesian infrence can improve in a significant way the localization performances; it has been proved on both simulated and real data.

1 Problem desctiption

Precise GNSS localization in urban environment is a key point for the developmement of a new generation of applications based on systems like GPS or Galileo. If some of the errors appearing in the positionning process can now be easily mitigated, like the tropospheric or ionospheric errors, this is not the case for local near-receiver errors like multipath which are one of the main source of errors. The reflection of the electromagnetic waves on obstacles implies the reception of non line-of-sight (NLOS) signals which induce an increase of the propagation time and therefore a bias

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in the final position estimation. It is all more true in urban environment because of buildings height, traffic jam or trees along main avenues for instance. If we study this problem from a dynamical system modelling point of view, we can show that this error comes from a measurement noise which is not gaussian but rather a mixture of gaussian ([2]). Multipath can then be mitigated using different approaches. The signal processing block can itself be improved by modifying the correlator block. But even in this case, it is hard to improve the estimation when only NLOS signals are received. Another solution consists in adding other sensors to the GNSS receiver : a fusion step then becomes necessary. But such a solution has a cost possibly high. We have therefore chosen to work on satellite-only systems with the aim a deriving a new generation of estimation algorithm based on an original statistical modelling of the error. A mixture can then be considered. It is however difficult to estimate a priori the right component number and practically we must estimate periodically a new mixture. Dirichlet Process Mixture (DPM) thus seems an interesting way to manage this problem. Using results of [1] on joint noise state estimation in dynamical systems it becomes possible to propose a bayesian estimation process for both measurement noise probability density function and localisation parameters.

2 Dynamical system modelling

The calculation of the position is based on the measurement of the so-called *pseudorange* p_m between each satellite and the receiver. For simplicity's sake we suppose the following relation between p_m and the parameters we need to estimate :

$$p_m(t) = \sqrt{(x(t) - x_s(t))^2 + (y(t) - y_s(t))^2 + (z(t) - z_s(t))^2} + w(t) = g(\mathbf{x}(t)) + w(t) \quad (1)$$

with $\mathbf{x}(t) = (x(t), y(t), z(t))$ the receiver position at a given time t in a given frame and $(x_s(t), y_s(t), z_s(t))$ the known satellite position. $w(t)$ is the measurement noise grouping the classical thermal noise and the noise coming from multipath. Such a relation exists for each satellite of the constallation (at least four) which can be received. The receiver dynamic can be modelled by a relation like $\mathbf{x}(t+1) = h(\mathbf{x}(t)) + v(t)$, where $t+1$ stands for the next sampling time, h is a known function (possibly non-linear) and $v(t)$ is the so-called state-noise.

3 Noise modelling using Dirichlet Process Mixture

We make the assumption that $w(t)$ is generated through the following hierachical model :

$$G \sim DP(\alpha, G_0)\ ,\ \theta(t)|G \sim G\ ,\ p_m(t) \sim f(p|\theta(t)) \quad (2)$$

where $DP(\alpha, G_0)$ is a Dirichlet Process with parameter α and base distribution G_0, f is a given probability density function (a gaussian in our case) and θ a parameter (the mean and the covariance of the gaussian law in our case). The Polya urn property of the Dirichlet process then allows the determination of a Rao-Balckwellized particle filter to estimate both θ and the state $\mathbf{x}(t)$ of the receiver ([1], [3]).

4 Results

The previous algorithm was implemented and tested on both simulated and real data. The simulated data represent two journeys in the French town Rouen and Toulouse. The real data were recorded in the town of Belfort. In all cases, the results show a real localization improvement in comparison with the classical Extended Kalman Filter and a particle filter using a classical fixed gaussian mixture as probability density function for the noise (see figure 3 and 4). The figure 5 shows the real trajectory and the estimated trajectory in Toulouse. Finally it is interesting to look at the clusters evolution with respect to time (see 6 : as we can see clusters are created or are moving when satellites states change from Line of Sight (LOS) to Non Line of Sight (NLOS) for instance.

5 Conclusion

Based on recent results of Non Parametric Bayesian approach in Signal Processing, our method brought in this application a real improvement that, to our knowledge, no previous work has reached.

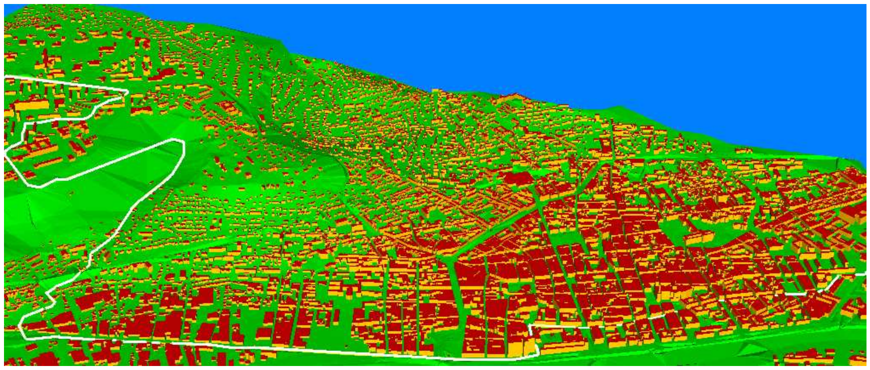

Figure 1: Simulated path through Rouen (France).

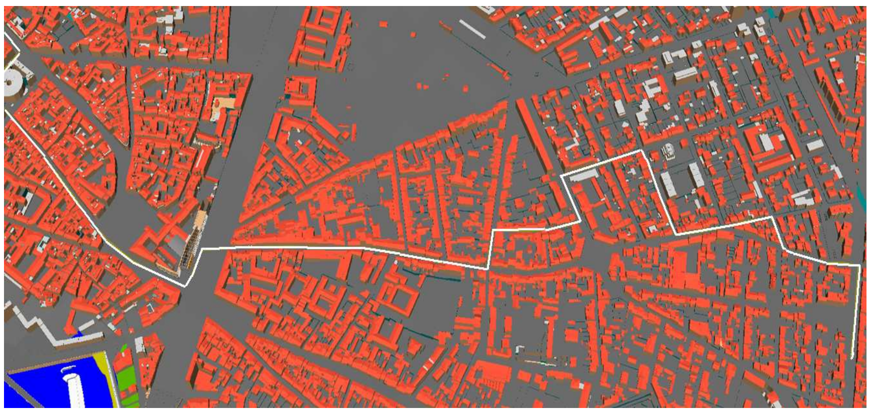

Figure 2: Simulated path through Toulouse (France).

We can point two improvements : on one hand the precision and on the other hand the adaptability to unknown and unforseeable situation. This is the strength of this method. Although several points still need to be improve. Of course this method can hardly be implemented in real time at the time being. Moreover theoritical analysis must still be carried out. For instance the errors on pseudo ranges are not independant wich strictly speaking, is one of the hypotheses of the underlying algorithm developped for non linear dynamical systems. Moreover, it is clear that clusters must be forgotten along the path. Finally, it coud be intersting to study the evolution of G_0 with respect to time and visibility situations. On this last point, first results have been obtained in [3]. As a result of this work, it seems that signal processing is a key area in which NPB results could be applied to bring new solutions to problems with unsatisfying solutions.

References

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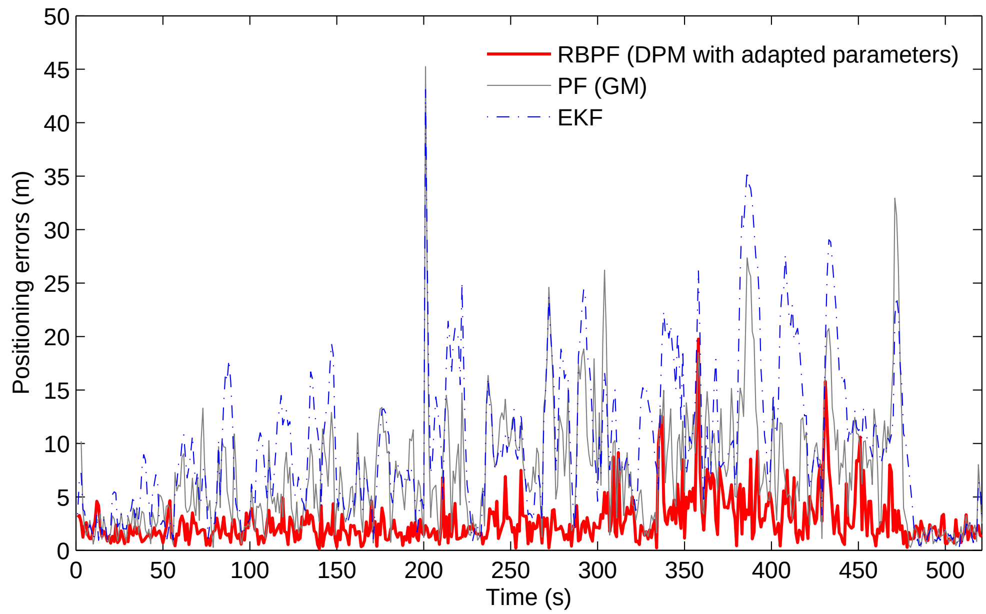

Figure 3: Localization error in Toulouse for the three methods implemented : DPM based method (red) overperforms the two others (blue = EKF and grey = particle filter.

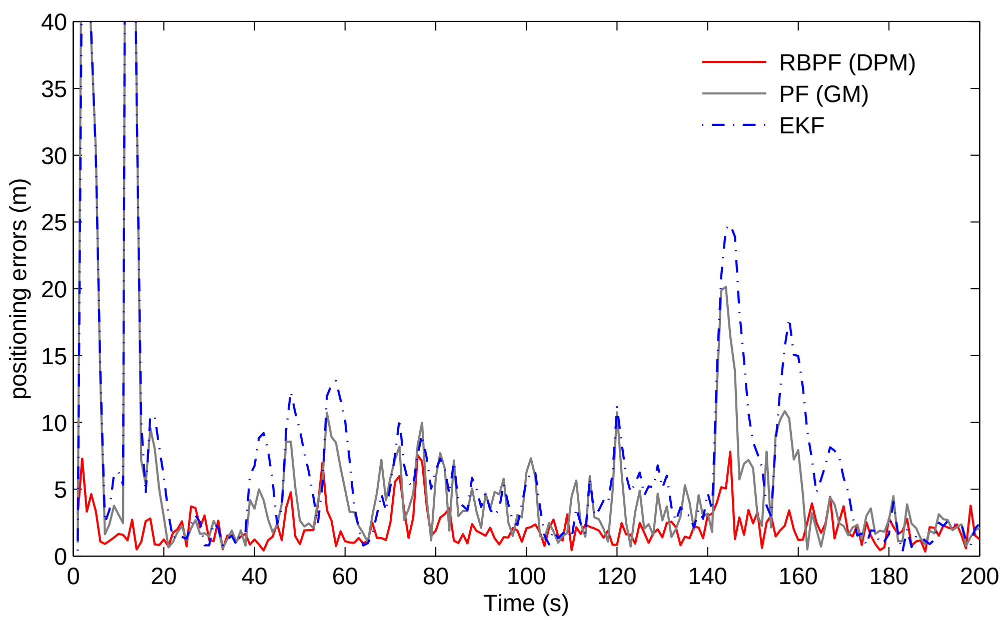

Figure 4: Localization error in Rouen for the three methods implemented : DPM based method (red) overperforms the two others (blue = EKF and grey = particle filter.

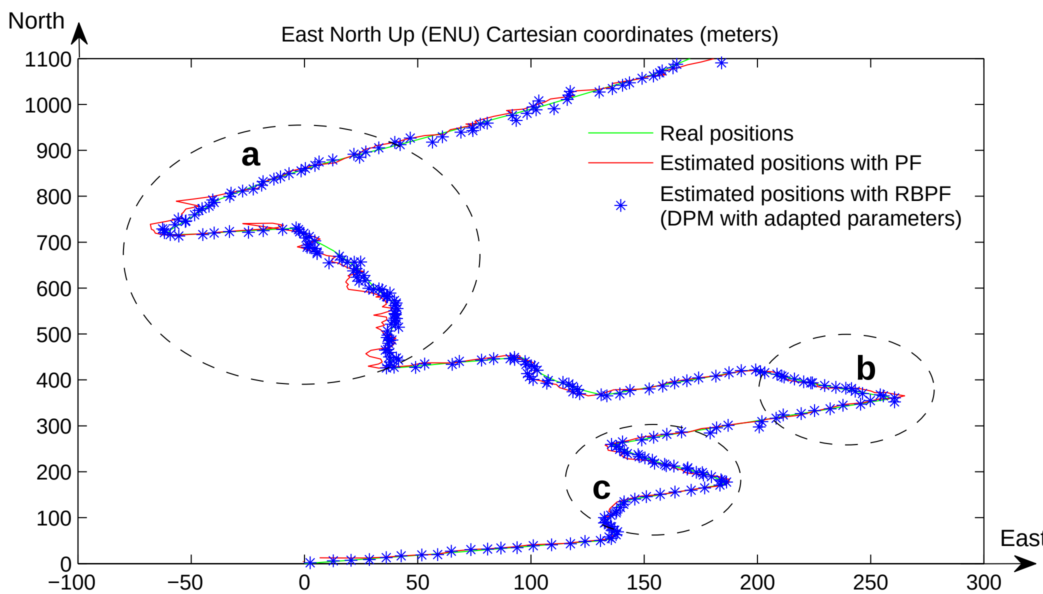

Figure 5: Real trajectory in Toulouse (green) and estimated trajectories : blue = DPM based method and red = particle filter based method

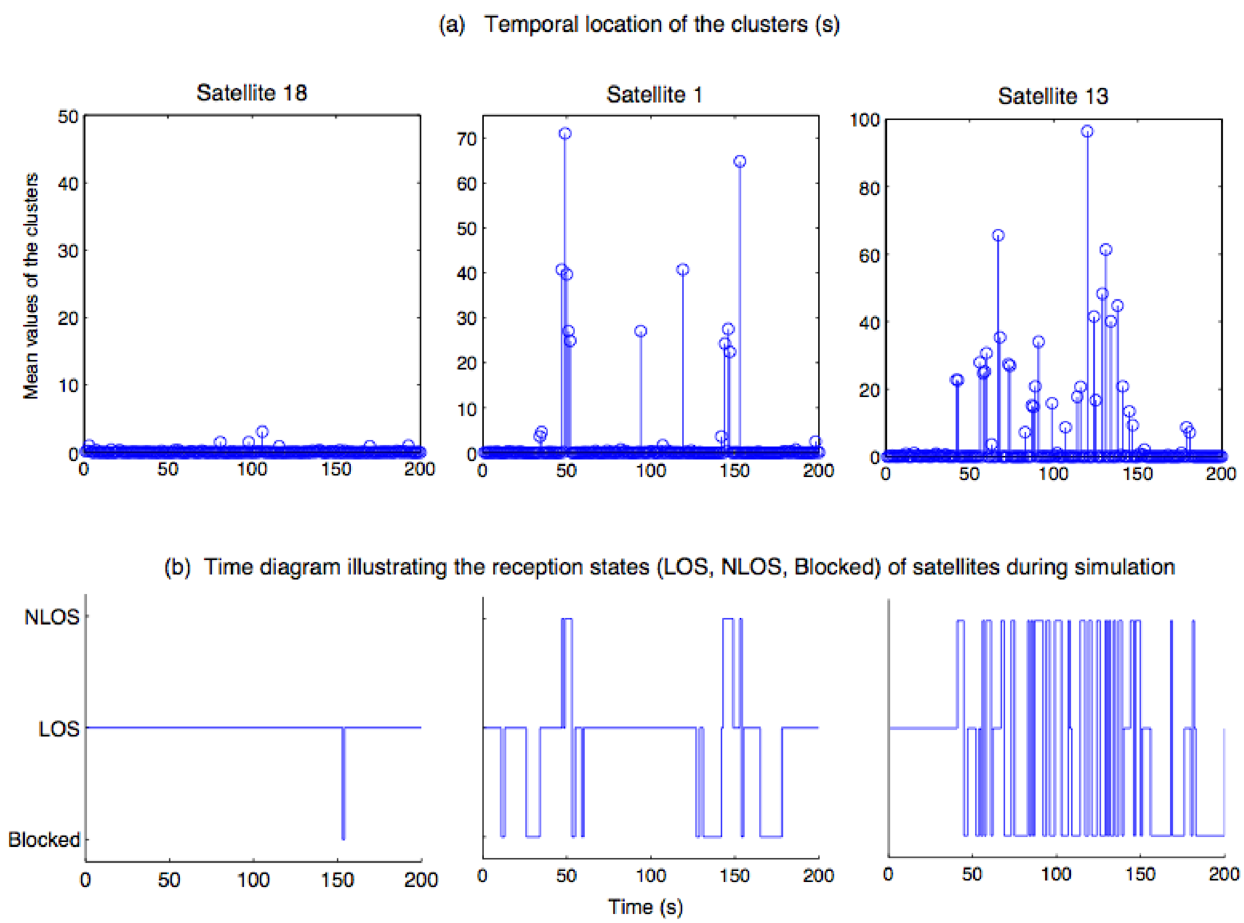

Figure 6: Evolution of the clusters for three satellites with respect to their visiblity from the receiver - LOS = Line of Sight - NLOS = Non Line of Sight - Blocked = invisible