The tracking loss rate (TLR) is defined as the ratio of the number of simulations, in which the target is lost in track (Maximum Position error $> 20[m]$) , to the total number of simulations carried out. The average CPU time (avg.CPU) is the CPU time needed to execute one time step in MATLAB R2011b (win64) on an Intel Core i7 (Nehalem microarchitecture) operating under Windows 7 Ultimate (Version 6.1). All the important specifications and features are reported in Table III.

TABLE III
SPECIFICATIONS & FEATURES

Processor	Type	Intel(R) Core(TM) i7
	Model	920
	Frequency	4.2 GHz
	Cores	4 (8 threads)
Memory	DRAM	6144 MB (3 x 2048 DDR3-SDRAM)
	Type	PC3-8500 (533 MHz)

VII. CONCLUSION

In this work, we propose an Interacting Population based Monte Carlo Markov Chain based PF (IP-MCMC-PF) that solves the multitarget tracking problem, which is fully parallelizable. In particular, the proposed algorithm matches the tracking performance of the multitarget SIR PF, while allowing for a dramatic reduction of the computational time.

Furthermore, we demonstrate through simulations that the proposed IP-MCMC-PF provides better tracking performance than the conventional MCMC based particle filter. This holds in terms of track accuracy and robustness to a low number of particles. In fact, sampling particles from the target posterior distribution via interacting population-based simulation avoids sample impoverishment and accelerates the MCMC convergence rate.

In a forthcoming work, we will therefore focus on more complex scenarios where targets may enter or leave the observation area. Furthermore, as future research we will investigate the applicability of well known MCMC techniques to additionally reduce the computational burden.

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