

# Phase locking of fiber laser array using quasi-reinforcement learning, principle and experiments

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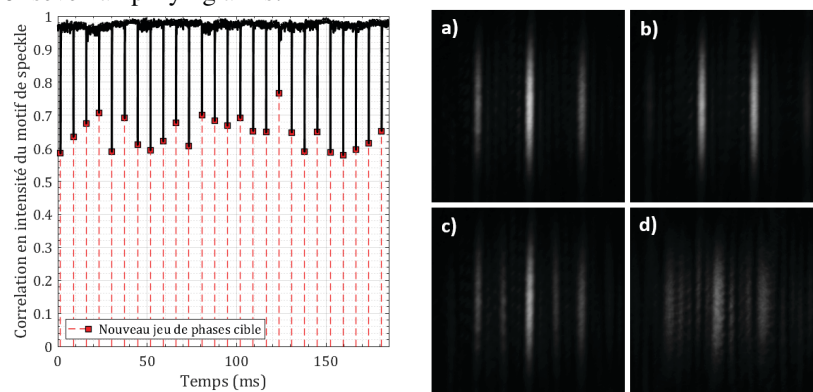
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Artificial intelligence is becoming more and more widespread in technological and scientific fields. Since 2019, it has extended to the coherent beam combining of laser array (CBC) [1], most of the time based on numerical studies. CBC is a key technique to reach high average power or high-energy short pulses while maintaining laser beam quality. In addition, the tiled-aperture arrangement of laser beam array offers the opportunity to shape this synthetic wavefront by setting the phase relationship between the individual beams in the array. We proposed a new technique to phase-lock on-demand and dynamically a laser array with a neural network learned in a phase correction loop. With this new iterative approach of “quasi-reinforcement learning”, we demonstrated the first experimental phase locking of a large one hundred laser beams [2]. This proof of principle experiment modelled the multiple beam phase noise in a static way. The neural network (NN) only required six phase corrections to lock the array on a target phase set whatever the initial phase relationships. With this first demonstration, the neural network was learned knowing the target phase set. We present an evolution of this architecture whose learning process is now adapted to lock a laser array on any phase set adaptively. This versatile architecture is experimentally validated by locking the phases of seven amplifying beams in a multiwatts fiber laser system [3].

The learning step occurs in an optimization loop like in [2]. The NN calculates the phase corrections to apply to the multiple parallel amplifying arms from sparse intensity data collected in a speckle field, interference pattern of the beams array through a diffuser. The new neuronal architecture is made of a first NN called “Target Adaptive Neural Network” (TANN) that provides the parameters of the second NN described in [2] depending on the target phase set. This second NN predicts the phase correction for the laser system. Its parameters can be changed and so the synthetic wavefront of the laser array, on-demand and quickly (product matrix-vector) via the TANN.

This couple of NN was implemented in a 10 kHz bandwidth feedback loop to drive the phase relationships of a fiber laser system of seven amplifying arms.



**Fig. 1** Left - Experimental sequence of periodic target phase changes showing the evolution of the speckle pattern intensity correlation. Right - Examples of experimental far field patterns of phase-locked fiber laser output

The experimental study shows that the phase correction only needs six iterations to converge to the target phase set, about 1.5kHz bandwidth, with a combining efficiency of 93%. Fig. 1 shows that synthetic wavefront can be shaped at the convergence speed about each one millisecond, useful property to pre-compensate propagation distortions through aberrating medium.

## References

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- [3] M. Shpakovych, et al, “On-Demand Phase Control of a 7-Fiber Amplifiers Array with Neural Network and Quasi-Reinforcement Learning” *Photonics*, **9**, 243, (2022)