



Digital Low Level Optical Control for Multidimensional Coherent Laser Combining

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2023/10/24 LLRF Workshop 2023



OCTOBER 22-27, 2023 In Gyeongju, Republic of Korea

Multi-dimensional coherent laser combining control

Enabling future laser plasma wakefield accelerator, and more scientific applications





Multi-dimensional Coherent Laser Combining control

- Temporal Stacking
 - 4 Cascaded optical cavities
 - 81 amplified pulse train
 - In-pulse gain saturation control
- Spatial Combining
 - 3x9 diffractional addition
 - deterministic pattern recognition
- Spectral Combining
 - Spectral amplitude control
 - Spectral phase control
- Fast interlock for machine protection



Mach Zehnder Interferometer, with feedback



Mach Zehnder Interferometer, as a beam combiner

Problem for feedback: phase ambiguity

Coherent optical receiver (heterodyne detection at 300THz)

Telecom approach, but maybe not suitable for us

- Too expensive for large number of channels
- Optical LO distribution and synchronization?
 - frequency comb?
- For multi-channel, free space combiner:
 - pointing stability?
 - beam profile variation?

A N×N beam combiner is almost too hard to control

01	Large dimensionality	 N**2 beams N**2 - 1 dimensional action space (phase)
02	Non-observable, Needs high precision	 Only beam powers are measurable Phase information are lost @ 300THz ~3 nm per degree of optical length control
03	Time variant, High noise bandwidth	 Beam power variation Pointing stability Polarization stability Phase noise bandwidth: ~10 kHz
04	Nonlinear, Non-uniqueness	 Detector dynamic range / saturation Many-to-one phase-pattern mapping

Popular solution: Stochastic Parallel Gradient Descent (SPGD, dither & search)

Our journey towards a scalable coherence control

Physics	Scalability	Robustness	Speed
 Identify control problems Discover optical physics Develop simulation Characterize experimental system Demonstrate 3x3 combining 	 Demonstrate 9x9 combining Demonstrate Neural Network based pattern recognition Solve: non-uniqueness, non-observable, non-linear 	 Develop model-free training against drift; Develop Deep Reinforcement Learning Demonstrate experimental stabilization Study 	 Develop FPGA accelerated deep learning controller: Xilinx DPU: 1µs High-level synthesize ML: 72ns Portable NN Engine: 1µs
BERKELEYLAR		Online-learning	10

Temporal Pulse Stacking Control

Coherently stack up-to-81 ultrafast laser pulses into one, using resonance optical cavities

Gires Tournois Interferometer (GTI) as resonance cavity

Coherence control by amplitude / phase modulation on each pulse at 1Gsps

GTI Optical Cavity physis

Control system model

Cascaded optical cavity phases are directly measured

using the first order digital filter characteristics

Single cavity impulse response

Cascaded cavity impulse response

FPGA based coherence control for 25 pulses stacking

IEEE J. Quantum Electron. 54:1, 2081 (2018)

81 pulse stacking using VC707+FMC120x2

Stabilization of cascaded optical cavity phase

1Gsps 8-in 8-out FPGA chassis

200ksps 8-in 8-out

81 pulses stacked Coherent Pulse Stacking Control

A. Rainville, M. Whittlesey, C. Pasquale, Y. Jing, Q. Du, and A. Galvanauskas, "Stable and Efficient Coherent Pulse Stacking Amplification of 81 Pulses with Four Channel Coherent Spatial Combining at 7mJ/Fiber," in CLEO 2023 SF3H.6.

81 pulses stacked with intensity RMS stability < 1%

Spatial Beam Combining Control

Coherently combining up to 81 parallelly amplified laser beams into one, by a single element

Filled Aperture Diffractive Optical Combining

DOE2

DOE1

Ο

Output Beam

Array

0 00

Need for many-in-many-out coherence control

0

00

Input Beam

Array

C

Fig. 1. Concept of the two-dimensional diffractive combiner.

Splitter

Oscillator

YDFA

Lens

Splitter

Superposition of waves

Opt. Lett. 42, 4422 (2017)

Opt. Lett. 43, 3269 (2018)

2-D, 8-way, ultrafast combiner

Free-space
 Fiber

2-D, 8-way, pattern recognition MIMO feedback

DOE transmission function

Opt. Lett. 44, 4554 (2019)

Identify optical combiner phase transfer function

40

Machine Vision based pattern recognition feedback

Opt. Lett. 44, 4554 (2019)

Discovered physics of diffractional beam combining

Complex valued matrix convolution:

$$\hat{s}(i,j) = \hat{b}(i,j) * \hat{d}(i,j)$$

Main plus side beams result from input beams convolved with DOE function

Phases drift, amplitudes not so much.

Efficient combination when:

$$\angle \hat{b}(i,j) = -\angle \hat{d}(-i,-j)$$

input beam phases equal DOE phase function,

but in reverse, because it's combining, not splitting

81 beams: a simple test bed for a complex problem

Computer generated hologram enables 9x9x6 degrees of freedom using Spatial Light Modulator

- Amplitude: Modulation depth
- Phase: Modulation start offset
- Angle X/Y: Modulation spatial freq. in x/y
- Shift X/Y: Modulation pixel position
- Beam spacing / shape / profile...

Hologram on SLM for generating 9x9 beams.

System identification: beam phase induced pattern

Phase scanning two-beam interference data reveals complex transmission function

Center + upper left beam

Center + Right beam

25

Intensity is function of DOE *modulated* beam phase

2 pairs of horizontal / vertical adjacent beam scannings completes the puzzle

BERKELEY LAB

9x9 diffraction transmission function characterized

15x15 transmission function (1st order 9x9)

Phase function accuracy: < 1.6 deg

- Power unit:
 - 1/81 of each input beam
- Amplitude unit:
 - 1/9 of each input beam

Scalability

81 beams combined experimentally

Simulated, center saturated

Measured, center saturated

measured

5000

4000

3000

2000

- 1000

Deep learning based active stabilization

Neural network translates a 17x17 diffraction pattern into a 9x9 phase error array

100

-100

100

-100

0

90

45

135 180

Training range can be a small fraction of phase space

Non-uniqueness problem addressed

Examples of same pattern generated by different phases

Training dataset phase range: ±40° around optimal

NN recognition even works outside training range

Prediction accuracy drops, but always > 50%

-2

ò

ż 4

150

- 100

-50

-100

-150

30

NN feedback is scalable, faster, no dither, more accurate

Demonstrated in simulation

Optics Express, 29(4) 5694, 2021

Shooting at a moving target: training in experiment

Training using orthogonally random dithering, faster than spontaneous phase drifting.

Feedback by predicted error using differential mapping

Training on pairing 2 patterns with a known dither

Optics Express, 30(8) 12639, 2022

Robustness

Experimentally combined 8 beams with < 0.4% RMS stability

(a) time history of output beam powers before and after activating stabilizer

7 250

200

150

100

- 50

250

200

150

100

- 50

0

(c) out-of-loop measurements of combined and side beam power

Optics Express, 30(8) 12639, 2022

ML@FPGA + Physics informed control platform

- Physics informed ML model, training against phase drift
- Al accelerator engine design and development (Larry Doolittle):
 - Support scalable NN structure with fully connected layers and ReLU activation (Multi-Layer Perceptron);
 - Works on any FPGA device;
 - Run-time configurable weights
 - Suitable for multi-input, multi-output, real-time feedback control
- Demonstrated quantized training, feedback control and FPGA inference in simulation:
 - Inference time: 131 cycles (1048 ns at 125MHz) for a 16-input, 8-output, 3 layer, 1600 parameters NN
 - Accuracy: 18-bits
 - Resource: 40 DSP48E and 40 BRAM18
- Closed loop in simulation
- Experiment development in progress

Spectral Beam Combining Control

Broadband spectral combining of three pulse-shaped fiber amplifiers with 42fs compressed pulse duration

Optics Express, 31(8) 12717, 2023

Conclusion

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stabilization

non-linear

• **Demonstrate** 3x3 combining

Thank you!

Collaborators: Tong Zhou, Russell Wilcox, Larry Doolittle, Dan Wang, Siyun Chen, U.Michigan team, et al.