

Nonlinear polarization effects in optical fiber-based extreme learning machines

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Abstract

Extreme learning machines (ELMs) based on nonlinear propagation in optical fiber are a novel platform for unconventional computing. However, although experiments are showing promising results, there has been less work developing realistic models to study how such systems might exploit different experimental degrees of freedom. Here, we use numerical simulations of the coupled vectorial generalized nonlinear Schrödinger equations to present the first study of fiber ELMs including polarization effects during propagation. Polarization evolution is found to significantly influence performance, necessitating care in polarization selection during readout. We also show that concatenating multiple polarization states during readout yields superior results compared to the analysis of a single state.

Optical fiber-based extreme learning machines (ELMs) perform task-specific computation by exploiting complex pulse propagation dynamics [1]. Specifically, information encoded on an input pulse undergoes dimensional-expansion through nonlinear and dispersive interactions during fiber propagation, with the broadened output spectrum serving as the effective hidden-layer of the ELM. Experiments have been reported by multiple groups [2–5], based on both anomalous-dispersion [6, 7] and normal-dispersion regime dynamics [8]. Numerical simulations using the scalar generalized nonlinear Schrödinger equation (GNLSE) have also examined how ELM performance depends on the physical system parameters [9, 10].

Here, we extend this work to present the first study of fiber-based ELM performance including vectorial (polarization) effects. We use coupled GNLSEs incorporating birefringence, Raman scattering, self-steepening, and higher-order dispersion [8, 11], and for the full MNIST handwritten digits dataset, we explore how ELM classification accuracy depends on input polarization state and different approaches to polarization-dependent readout. We consider propagation for both anomalous and normal dispersion. We show that polarization effects can degrade ELM accuracy unless input and output states are properly optimized. We also show that further increase in accuracy can be obtained by concatenating multiple polarization states during readout to introduce additional dimensional expansion.

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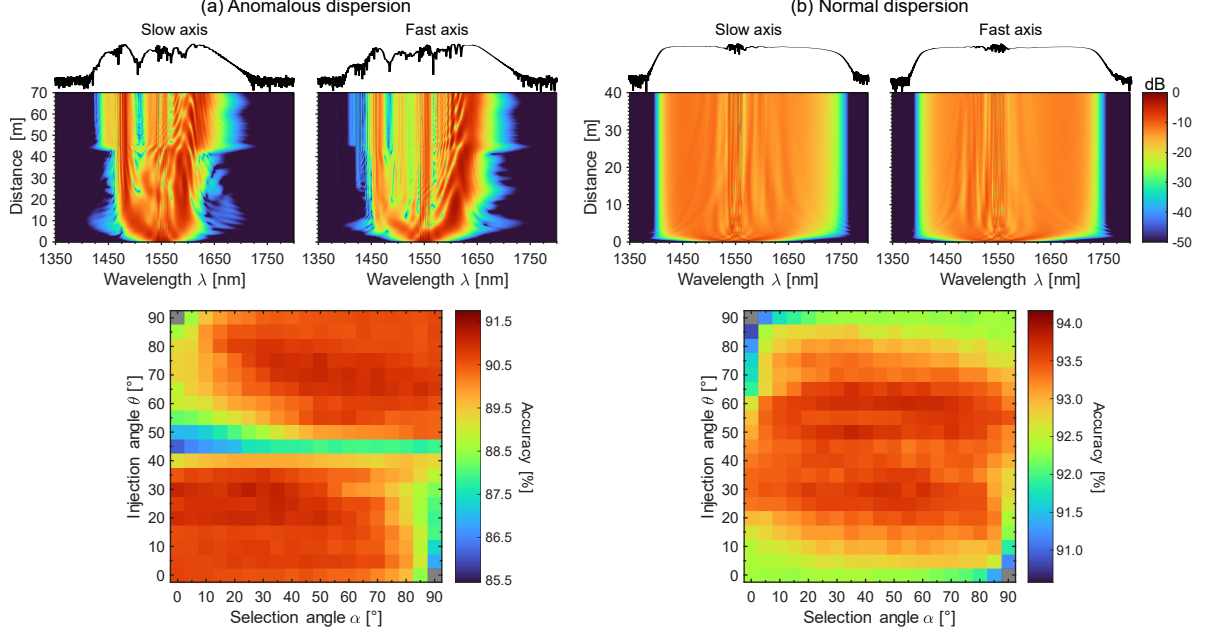


FIG. 1. (a) and (b) show results for anomalous and normal dispersion respectively for constant birefringence $\Delta n = 10^{-5}$. Upper plots show spectral evolution on slow and fast fiber eigenaxes as indicated for input launch angle of 45° . The heatmaps plot MNIST classification accuracy varying the linear polarization angle of the injected input pulses (vertical axis) and for different polarization selection readout angles for the output spectra (horizontal axis). Note the different colorbar scales of (a) and (b). The gray corner pixels of the heatmaps are not used for readout (see text).

Our simulations solve the coupled GNLSEs previously used to model vectorial supercontinuum generation [8, 11, 12]. For circular polarization components u_1 and u_2 , we have:

$$\begin{aligned}
\frac{\partial u_j}{\partial z} = & \left(i \frac{\Delta \beta_0}{2} - \frac{\Delta \beta_1}{2} \frac{\partial}{\partial \tau} \right) u_{3-j} \\
& - i \left(\frac{\beta_2}{2!} \frac{\partial^2}{\partial \tau^2} + i \frac{\beta_3}{3!} \frac{\partial^3}{\partial \tau^3} + \dots \right) u_j \\
& + i \gamma \left(1 + \frac{i}{\omega_0} \frac{\partial}{\partial \tau} \right) \left\{ (1 - f_R) \left(\frac{2}{3} |u_j|^2 + \frac{4}{3} |u_{3-j}|^2 \right) u_j \right. \\
& \left. + f_R u_j \int_{-\infty}^{\tau} h_R(\tau - \tau') [|u_j(\tau')|^2 + |u_{3-j}(\tau')|^2] d\tau' \right\}.
\end{aligned}$$

Here the component indices are $j = 1, 2$, z is distance, τ is time, the β_k are the k^{th} -order dispersion coefficients at ω_0 , the angular frequency corresponding to a pump wavelength of 1550 nm. Parameter γ is the nonlinear coefficient and h_R the experimental Raman response of silica [11] with $f_R = 0.18$. The linear field components along principal axes x (slow) and

y (fast) are $E_x = [(u_1 + u_2)/\sqrt{2}] \exp(-i\Delta\beta_0 z/2)$, and $E_y = [(u_1 - u_2)/i\sqrt{2}] \exp(i\Delta\beta_0 z/2)$. The birefringence-induced phase and group mismatches are $\Delta\beta_0$ and $\Delta\beta_1$ respectively, with $\Delta\beta_0 = \omega_0\Delta n/c$ and $\Delta\beta_1 = v_x^{-1} - v_y^{-1}$. $\Delta n = n_x - n_y$ is the refractive-index difference and v_x and v_y are the group velocities along the two axes. We consider fiber properties as in Ref. [9], specifically: for anomalous-dispersion regime propagation in 70 m fiber, $\beta_2 = -0.12 \text{ ps}^2\text{km}^{-1}$; $\beta_3 = 0.040 \text{ ps}^3\text{km}^{-1}$; $\beta_4 = 0 \text{ ps}^4\text{km}^{-1}$; $\gamma = 10.7 \text{ W}^{-1}\text{km}^{-1}$; for normal-dispersion regime propagation in 40 m of fiber, $\beta_2 = 0.987 \text{ ps}^2\text{km}^{-1}$; $\beta_3 = 7.31 \times 10^{-3} \text{ ps}^3\text{km}^{-1}$; $\beta_4 = 4.10 \times 10^{-4} \text{ ps}^4\text{km}^{-1}$; $\gamma = 7.5 \text{ W}^{-1}\text{km}^{-1}$. We used linearly-polarized input pulses with Jones matrices applied to vary the input polarization relative to the fiber principal axes, as well as to analyze the polarization properties of the output along specific directions as discussed below. Input pulse quantum noise is included via a semiclassical model [13].

To model MNIST digit classification using a fiber-ELM, we proceed as follows [9]. A length-100 representation of an MNIST handwritten digit image (downsampled after bicubic interpolation) is scaled to a maximum value of 0.25π and used to spectrally phase-encode a pulse prior to fiber injection. This models the use of an SLM-based spectral phase mask in experiments [5]. The pulse is constructed from a supergaussian spectrum with 30 nm bandwidth (FWHM) and $\Delta\tau \approx 180$ fs temporal duration (FWHM). The peak power is ~ 105 W or ~ 1230 W for anomalous- or normal-dispersion regime propagation respectively, corresponding to $N = (\gamma P_0 T_0^2 / |\beta_2|)^{1/2} \sim 10$. Here $T_0 = \Delta\tau/1.76$, and N is a measure of nonlinear strength (corresponding to soliton number for anomalous dispersion).

For a given injection angle (relative to the slow axis), simulations model the complex coupled dynamics and associated spectral broadening. This is repeated for 60,000 training images to yield an effective hidden-layer matrix of 60,000 broadened spectra. The readout step uses the 2048-length output spectral intensities computed from simulations, convolved with a 1 nm (FWHM) gaussian spectral response and with addition of a -30 dB noise floor [9]. Since we know the digit labels for the MNIST data, the output layer weight matrix can be computed in one step via regression. Comparable results are obtained using either Penrose-Moore or ridge regression for our data [9]. Performance is then evaluated

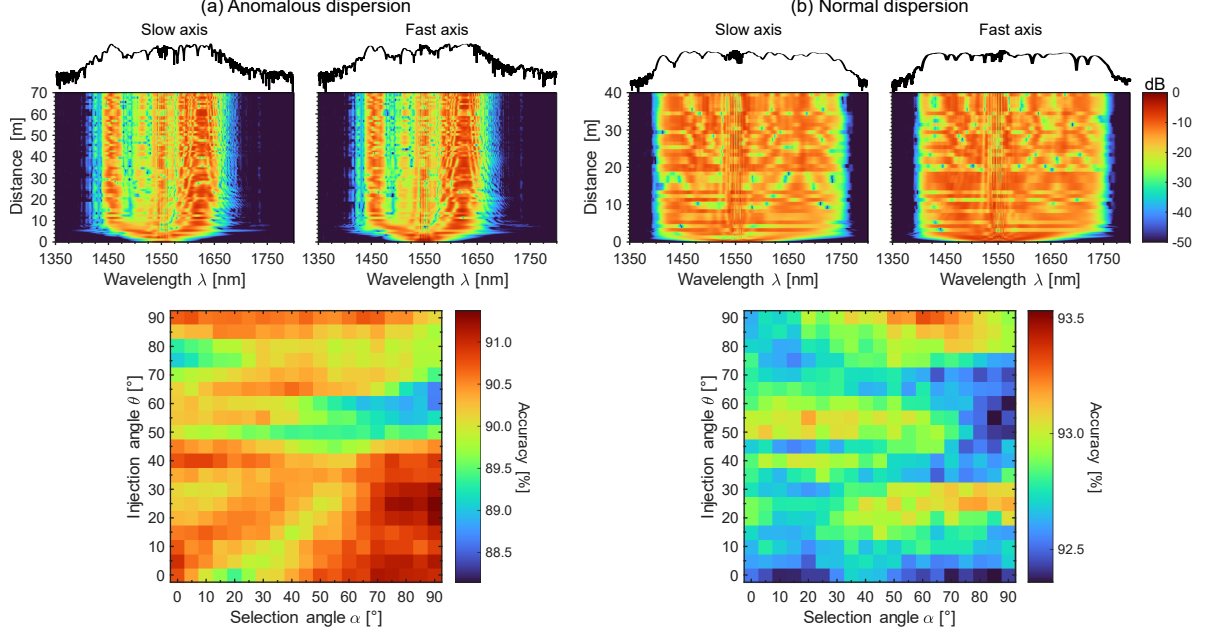


FIG. 2. (a) and (b) show results for anomalous and normal dispersion respectively for randomly-varying birefringence on a 1 m distance scale. Upper plots show spectral evolution on slow and fast fiber eigenaxes as indicated for input launch angle of 45° . The heatmaps plot MNIST classification accuracy varying the linear polarization angle of the injected input pulses (vertical axis) and for different polarization selection readout angles for the output spectra (horizontal axis). Note the different colorbar scales of (a) and (b).

by applying the weight matrix to a validation set of 10,000 spectra generated from input pulses encoded using previously unseen images, and comparing the predicted digits with the known input labels.

To illustrate the general features of the coupled vectorial dynamics, we first consider a fiber with longitudinally constant birefringence of $\Delta n = 10^{-5}$ [11]. With parameters as above and for an input pulse launched at 45° , the upper plots in Figs 1(a) and (b) show the spectral evolution along each eigenaxis for anomalous- and normal-dispersion regimes respectively. The different evolution dynamics on each axis arise from the differing linear dispersion properties on each axis, walk-off between polarization components, and cross-phase modulation [8]. The previous studies in Ref. [11] have shown that these coupled dynamics depend sensitively on input injection angle, and to study how this may impact ELM accuracy, we performed simulations for different injection and readout angles using the training and testing procedure described above. Specifically, we varied the input injection

angles from 0–90° (relative to the slow axis) and, after propagation, we constructed different hidden layer matrices at the readout step by projecting the output spectra along a different polarization direction, also spanning over 0–90°. In practice the injection step would be implemented with a half-wave plate, and the readout step with a linear polarizer.

Figures 1(a) and (b) show ELM accuracy heatmaps obtained from this procedure, using different colorbar scales in each case. The gray corner pixels of the heatmaps are not useful for readout because they correspond to the cross-polarization points where we inject on one axis and analyze on the orthogonal axis. In this case there is negligible energy transfer between axes, and readout is performed essentially on a noise field. The ELM accuracy was further quantified by a cross-validation step using random partitioning of the simulations into 5 different training and testing datasets to compute a mean accuracy. The qualitative heatmap features obtained were confirmed to be independent of this partitioning (see Sec. I), but the mean accuracies at each point should be associated with $\pm 0.2\%$ standard deviation. All results given below use this procedure.

For this level of downsampling of the MNIST dataset, the linear regression benchmark in the absence of any nonlinear propagation was $\sim 85.5\%$, and we clearly see that the accuracies in the heatmaps exceed this significantly over large regions of input and analyzer angles. These results clearly show how accuracy depends on both the input and readout polarization angles, and the improved results seen in the normal dispersion regime are consistent with previous experiments and scalar-GNLSE simulations [2, 4, 5, 9].

The dependence of accuracy on polarization is more marked for anomalous-dispersion regime propagation, where Fig. 1(a) shows a dip in performance around an injection angle of 45°, and higher accuracy for injection angles around e.g. 20° or 70°. This can be understood in terms of the effect of the injection angle on the power distribution (soliton number) between the principal axes, which impacts both the soliton fission dynamics on each axis, as well as the nonlinear coupling between the axes [6, 11]. In contrast, the results for normal dispersion regime propagation in Fig. 1(b) show higher overall accuracy and a more uniform performance landscape. The reduced sensitivity to the injection angle for normal dispersion suggests that the spectral broadening mechanisms here (self-phase modulation and optical

(a) Test accuracies (%) for constant birefringence			(b) Test accuracies (%) for random birefringence		
	Anom. Disp.	Norm. Disp.		Anom. Disp.	Norm. Disp.
M = 1 (2048 pts)	91.2	93.8	M = 1 (2048 pts)	91.4	93.3
M = 2 (4096 pts)	92.7	94.6	M = 2 (4096 pts)	93.2	94.8
M = 3 (6144 pts)	93.1	95.2	M = 3 (6144 pts)	93.7	95.2
M = 4 (8192 pts)	93.0	95.2	M = 4 (8192 pts)	93.5	95.2
M = 5 (10240 pts)	92.6	95.1	M = 5 (10240 pts)	93.3	95.0
M = 2 (2048 pts)	92.6	94.5	M = 2 (2048 pts)	93.2	94.6
M = 3 (2048 pts)	92.6	94.9	M = 3 (2048 pts)	93.3	94.8
M = 4 (2048 pts)	92.6	94.8	M = 4 (2048 pts)	93.2	94.9
M = 5 (2048 pts)	92.4	94.8	M = 5 (2048 pts)	93.2	94.9

TABLE I. Summary of fiber-ELM test accuracies for (a) constant and (b) random birefringence. Parameter M describes the number of concatenated spectra used at readout. The single spectrum case ($M = 1$ with 2048 points) is shaded, and the upper tables show results for multiple-angle concatenations ($M = 2$ –5) with an increasing number of total points. The bottom tables show the accuracies when the multiple-angle concatenated matrices are uniformly downsampled to 2048 points.

wave breaking) are less sensitive to the power-splitting ratio than soliton fission. Note that in both cases, some dependence on the analyzer angle is also observed, highlighting that optimizing both injection and readout angles is necessary for best accuracy. For completeness, we note that the highest test accuracies for anomalous and normal dispersion were 91.2% and 93.8% respectively.

Unless particular care is taken with polarization control in an experiment, more realistic modeling would need to consider some form of randomly-varying birefringence in the fiber. To this end, we modified the simulations above to randomly rotate the polarization eigenaxes (angle drawn from $[0, 360^\circ]$) after every 1 m of propagation using a coarse-step method [14]. Birefringence ($\Delta n = 10^{-5}$) was kept the same for each segment. Although this is a highly simplified model of stochastic polarization evolution [15], it nonetheless captures the essential impact of random polarization scrambling on ELM performance. Results for anomalous and normal dispersion in this case are shown in Figs 2(a) and (b) respectively, where we again plot the spectral evolution of one typical simulation, as well as the accuracy heatmaps obtained after post-processing the full dataset. The effect of random birefringence is very clear from the evolution plots, and we see how the the birefringence variation introduces more structure into the spectra on both axes.

The accuracy heatmaps reveal significant differences from the results in Fig. 1 and, in

particular, for the anomalous-dispersion regime case in Fig. 2(a), the performance dip previously observed around a 45° injection angle is largely suppressed. This suggests that the random rotation of the principal axes averages out the sensitive dependence of soliton fission dynamics on the initial power-splitting ratio. For the normal dispersion regime as shown in Fig. 2(b), the ELM maintains superior performance compared to the anomalous-dispersion regime, attributed to the robustness of the wave-breaking dynamics to random polarization rotations. This further reinforces the practical advantages of normal-dispersion fibers for physical ELM systems in the absence of precise polarization control. The highest test accuracies for anomalous and normal dispersion in this case were 91.4% and 93.3% respectively, comparable to the constant birefringence case. The heatmap topologies shown in Fig. 2 of course correspond to only a single set of random axes rotation angles along the fiber, and additional simulations showed that different selections of random angles yielded heatmaps with different detailed structures (see Sec. I). However, the maximum accuracies obtained were comparable.

Exploiting polarization-sensitive dynamics in a fiber-ELM suggests the additional possibility to increase dimensionality at the readout step by concatenating different output spectra measured at different analyzer angles. For example, combining spectra measured at M different angles would result in a hidden layer matrix of size $(M \times 2048) \times 60,000$, which might well be expected to yield improved performance, provided of course that the multiple-angle readout captures non-redundant spectral features. To test this, we concatenated spectra for several multiple-angle configurations: $M = 2$ ($0^\circ, 90^\circ$), $M = 3$ ($0^\circ, 45^\circ, 90^\circ$), $M = 4$ ($0^\circ, 30^\circ, 60^\circ, 90^\circ$), and $M = 5$ ($0^\circ, 22.5^\circ, 45^\circ, 67.5^\circ, 90^\circ$), and performed the training and testing procedure as above. In this case, we might immediately expect improved performance because of the increased matrix dimensionality, and so to provide an additional comparison with the single angle readout case, we also tested performance by uniformly downsampling (using linear interpolation) each expanded matrix to 2048 spectral points, the same size as the single-angle case.

Table I summarizes the results of this procedure for propagation in (a) constant and (b) random birefringence fiber for anomalous and normal dispersion as labeled. The gray

shaded results in each case are the single-spectra accuracies without concatenation (as given above). Considering first the upper tables for the concatenation of different numbers of spectra without downsampling (i.e. an increasing number of points), we see how concatenation yields improved accuracies for both anomalous and normal dispersion. A similar trend is seen for random birefringence. Importantly, the downsampled results (in the bottom tables) confirm that these gains are not simply a consequence of increased matrix dimensionality: even when the concatenated matrices are downsampled to 2048 spectral points, the accuracies obtained still exceed the single-angle benchmark. This suggests that the multiple-angle readout (polarization diversity) genuinely captures non-redundant spectral information. We also remark that across all regimes, accuracy appears to saturate around $M \sim 3\text{--}4$, suggesting that three to four analyzer angles provide a near-optimal balance between performance and experimental complexity.

In conclusion, these results have shown that polarization can play a critical role in determining fiber-ELM performance, with both the input state and readout configuration strongly influencing classification accuracy. However, while polarization sensitivity can degrade performance under non-optimized conditions, it also provides an additional degree of freedom that can be exploited to yield improved results. In particular, multi-angle polarization readout yields consistent improvement in accuracy, even when controlling for the number of features.

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I. SUPPLEMENTAL MATERIAL

This section presents additional material relating to nonlinear polarization effects in fiber-based extreme learning machines (ELM). This includes: (i) confirmation that the results obtained above are independent of the partitioning between training and testing datasets; (ii) the presentation of results for the case of random birefringence using different choices of random axes rotations along the propagation length.

A. Results of cross-validation using dataset partitioning

All results presented above were obtained by evaluating the ELM performance using a single 60,000/10,000 training/testing split of MNIST-image based supercontinuum spectra. Here, we study how those results vary as we randomly select different 60,000/10,000 partitions from the full 70,000-image MNIST library.

Figure 1 above plots heatmaps showing the ELM performance (test accuracy) as a function of the input linear polarization angle, and for different polarization selection readout angles for the output spectra. In Figs. 3 and 4 below, we show a selection of 5 additional heatmaps for 5 random 60,000/10,000 partitions. Here Fig. 3 corresponds to propagation in the anomalous dispersion regime (to be compared with Fig. 1(a)) and Fig. 4 corresponds to propagation in the normal dispersion regime (to be compared with Fig. 1(b)). As above, the heatmaps plot MNIST classification accuracy from the test dataset varying the linear polarization angle of the injected input pulses (vertical axis) and for different polarization selection readout angles for the output spectra (horizontal axis). As might be expected, the results show quantitative differences for the different choices of partitions, but the overall features of the heatmaps remain qualitatively similar. Evaluated over a total of 5 partitions, we are able to associate a $\pm 0.2\%$ standard deviation associated with the accuracies shown.

B. Results for different random axes rotations

Figure 2 above shows results for ELM performance with randomly-varying birefringence on a 1 m distance scale. Of course, the heatmap topologies shown in Fig. 2 correspond to only a single choice of random axes rotation angles along the fiber, and additional simulations showed that different selections of random angles yielded heatmaps with different detailed structure. However, the maximum accuracies obtained were comparable.

For example, for the case of anomalous dispersion shown in Fig. 2(a) above, Fig. 5 shows results from additional sets of simulations corresponding to two different selections of random axes rotations. The top figures in each case show the spectral evolution on the slow and fast fiber eigenaxes as indicated for an input launch angle of 45° . The heatmaps plot MNIST classification accuracy varying the linear polarization angle of the injected input pulses (vertical axis) and for different polarization selection readout angles for the output spectra (horizontal axis). These results are to be compared with Fig. 1(a) above.

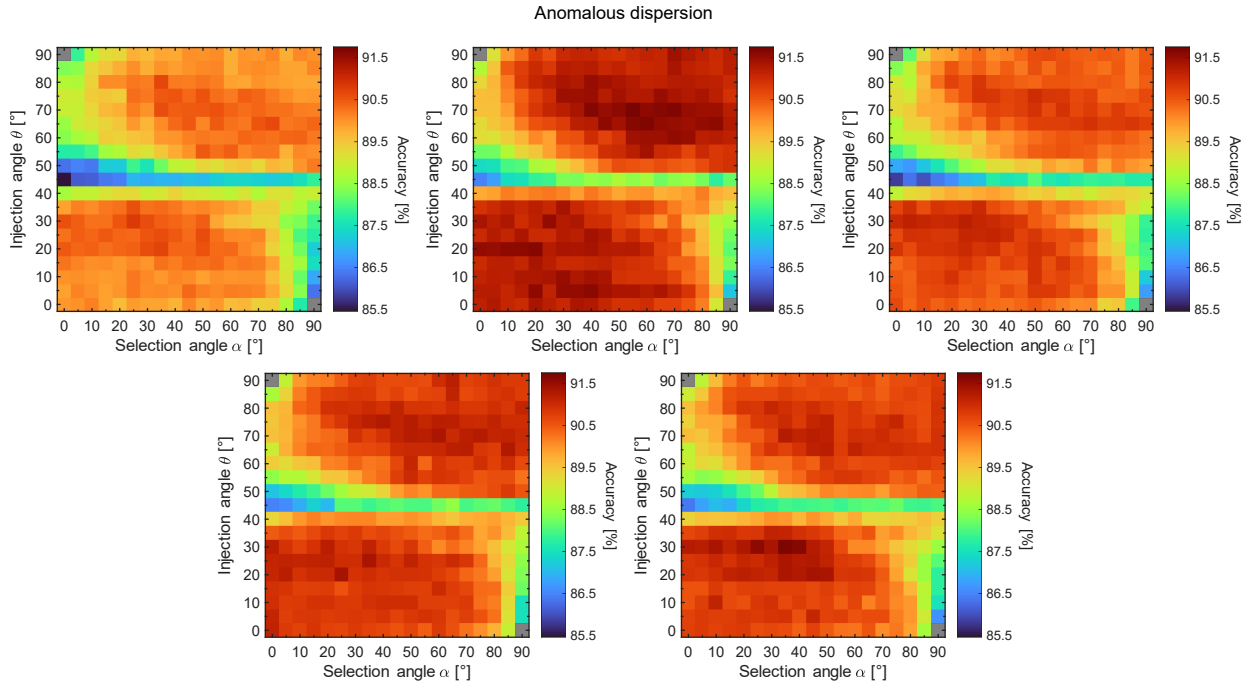


FIG. 3. For anomalous dispersion, we show 5 different accuracy heatmaps for different 60,000/10,000 partitions of training and testing datasets. The heatmaps plot classification accuracy varying the linear polarization angle of the injected input pulses (vertical axis) and for different polarization readout angles for the output spectra (horizontal axis). These results are to be compared with Fig. 1(a) above.

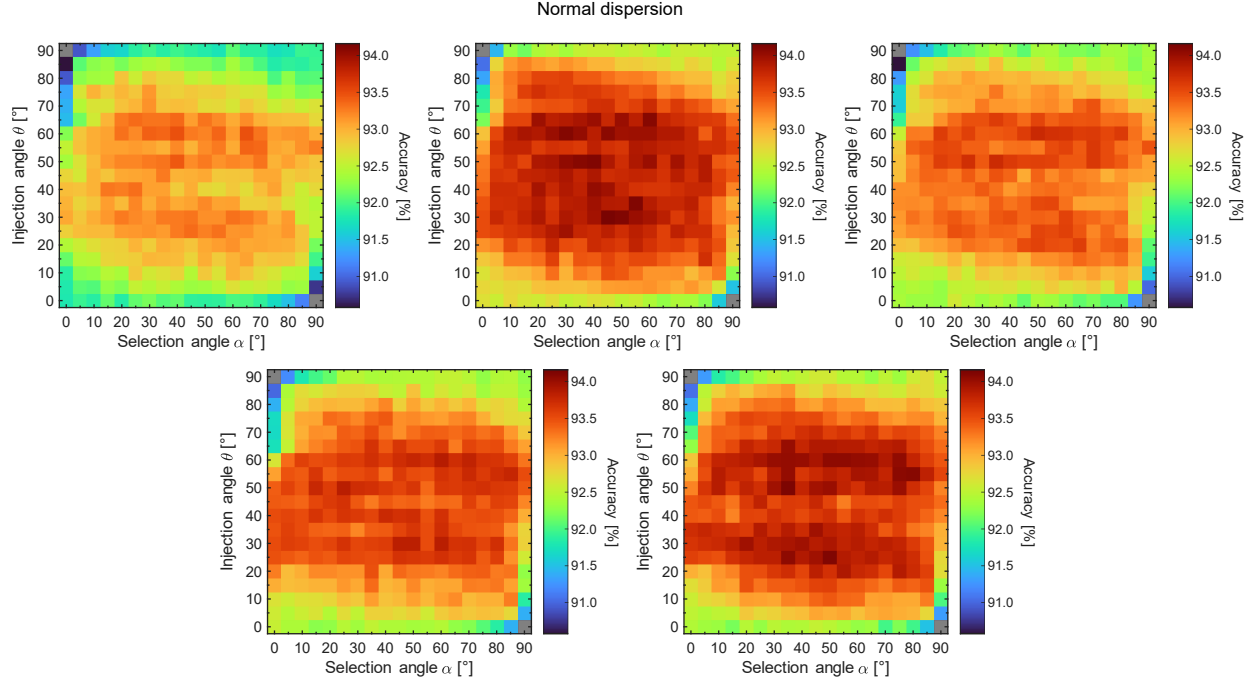


FIG. 4. For normal dispersion, we show 5 different accuracy heatmaps for different 60,000/10,000 partitions of training and testing datasets. The heatmaps plot classification accuracy varying the linear polarization angle of the injected input pulses (vertical axis) and for different polarization readout angles for the output spectra (horizontal axis). These results are to be compared with Fig. 1(b) above.

spectra (horizontal axis). These results show how the regions of high and low accuracy in the heatmap occur at different combinations of input and analyzer angles, but the maximum accuracy is comparable at $\sim 91.5\%$. Fig. 6 shows comparable results for the case of normal dispersion with maximum accuracy of $\sim 93.5\%$ comparable to that in Fig. 2(b) above.

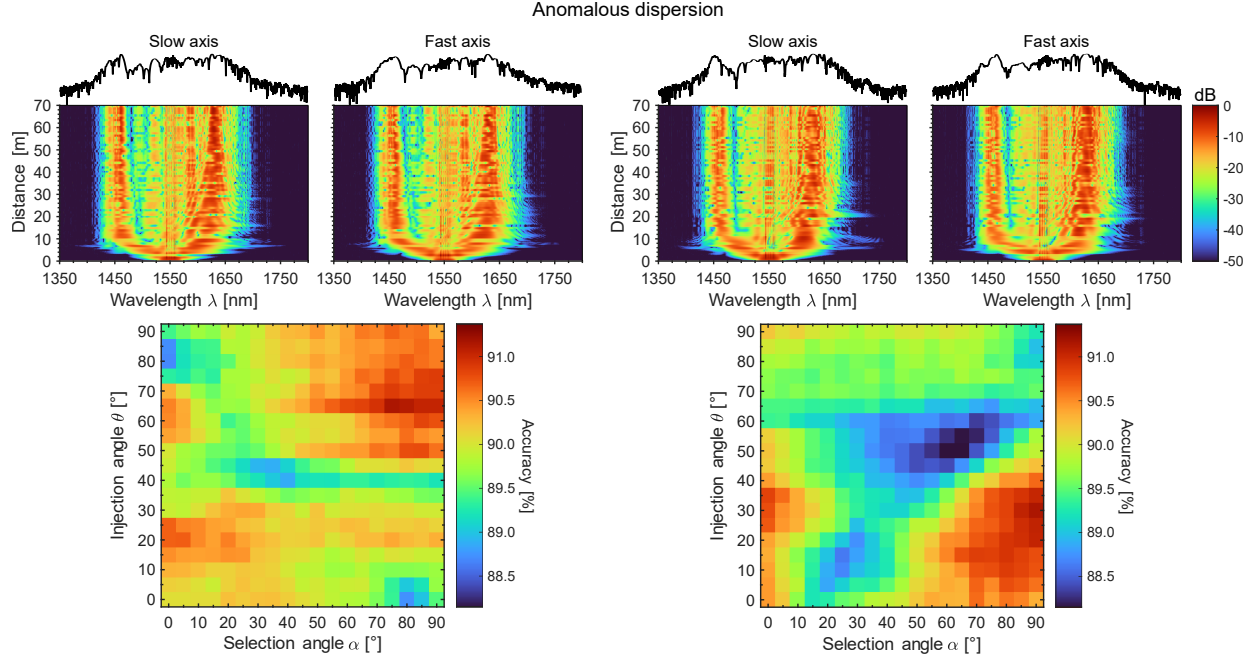


FIG. 5. Complementing the results in Fig. 2(a) above, the figure shows results for anomalous dispersion regime propagation for two additional cases of randomly-varying birefringence on a 1 m distance scale. The upper plots show spectral evolution on slow and fast fiber eigenaxes as indicated for input launch angle of 45° . The heatmaps plot MNIST classification accuracy varying the linear polarization angle of the injected input pulses (vertical axis) and for different polarization selection readout angles for the output spectra (horizontal axis).

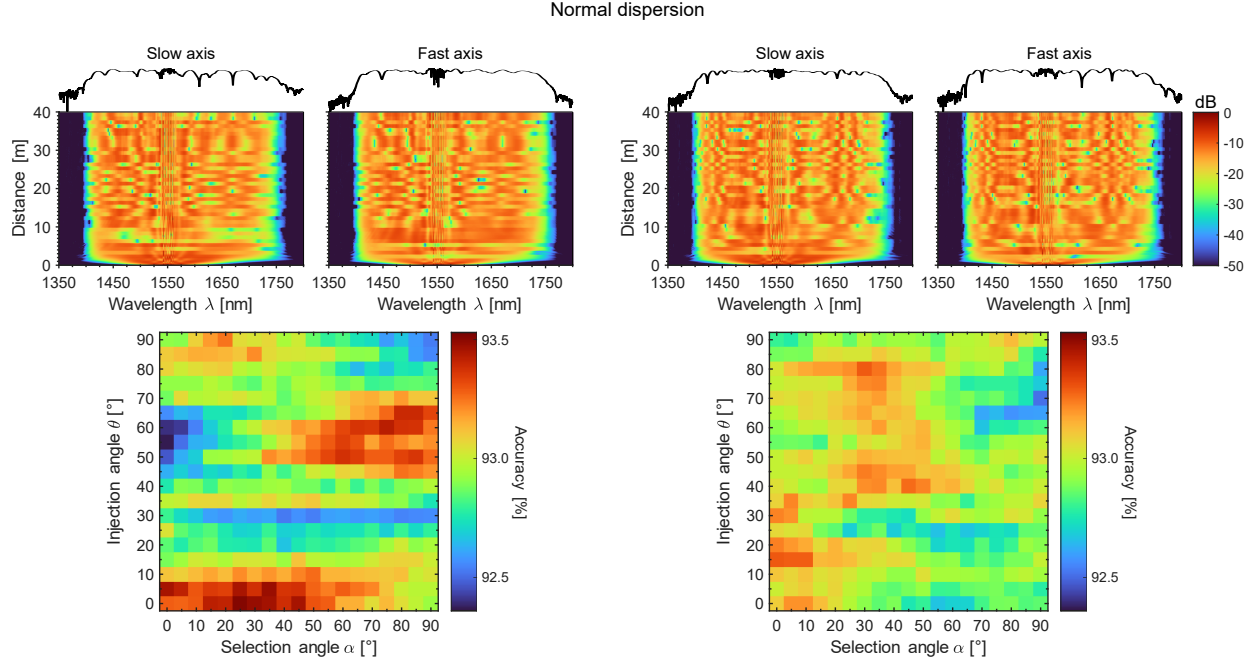


FIG. 6. Complementing the results in Fig. 2(b) above, the figure shows results for normal dispersion regime propagation for two additional cases of randomly-varying birefringence on a 1 m distance scale. The upper plots show spectral evolution on slow and fast fiber eigenaxes as indicated for input launch angle of 45° . The heatmaps plot MNIST classification accuracy varying the linear polarization angle of the injected input pulses (vertical axis) and for different polarization selection readout angles for the output spectra (horizontal axis).

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