

Clinical Polarimetry: Identifying Minimal Mueller Subsets to increase imaging speed

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ABSTRACT

Polarimetric imaging offers rich contrast for tissue discrimination, yet full 4×4 Mueller acquisition remains slow and hardware intensive. We investigate which practical subsets of the Mueller matrix preserve diagnostic power, potentially enabling faster, simpler systems. Using decision tree classifiers, we benchmark reduced-configuration models that simulate realistic hardware choices (with/without quarter-wave plates (QWPs) in the Polarisation State Generator (PSG)/Polarisation State Analyser (PSA); targeted row/column recovery) across five diverse biomedical domains: neurosurgical brain (PoLambRimetry), colorectal cancer (ColoPola), dermatology (Mice Skin Tumour, non-melanoma), hepatology (Liver Cancer, hepatocellular carcinoma (HCC) vs intrahepatic cholangiocarcinoma (ICC)), and breast oncology (healthy vs tumour). Across datasets, combinational subsets that omit one or both QWPs (linear PSG and/or linear PSA) often retain near-baseline performance, indicating that 3×4 , 4×3 and 3×3 configurations can be highly competitive. These reductions can offer significant speed-ups (and simpler instruments/mechanics/calibration) with minimal loss in classification accuracy on several tasks. Importantly, we observe dataset-dependent variability in which subsets dominate. Practically, our findings support streamlined designs: (i) linear-only PSG/PSA systems for many classification tasks; (ii) targeted recovery of specific rows/columns prioritizing high-utility linear elements; and (iii) task-specific additions of circular states where they measurably help. This cross-domain evidence suggests that reduced Mueller polarimetry can deliver clinically relevant discrimination while cutting measurements, speeding acquisition, and shrinking system complexity, lowering barriers to adoption in clinical specimen imaging workflows.

Keywords: Mueller polarimetry, Machine learning, Snapshot polarimetry, Real-time imaging, Clinical polarimetry

1. INTRODUCTION

In the Stokes-Mueller formalism, the polarization state of light is represented by a Stokes vector $S \in R^{4 \times 1}$ and an optical sample is represented by a Mueller matrix $M \in R^{4 \times 4}$ that maps incident to emergent Stokes vectors:

$$S_{\text{out}} = MS_{\text{in}} \quad (1)$$

In Mueller matrix imaging, each pixel (x, y) , where x is the height and y the width, can be associated with its own Mueller matrix $M(x, y)$, producing a 16 channel image representation which can be directly used for downstream analysis or deriving polarimetric parameters.

Mueller matrix imaging is attractive for biomedical applications because polarized light interactions encode tissue microstructure and composition. Scattering, depolarization, and birefringence can produce diagnostically useful contrast, and prior studies have shown that discriminative information is often concentrated in specific Mueller elements rather than being uniformly distributed across the full matrix.¹⁻⁴ This suggests that full 4×4 acquisition may not always be necessary for a given diagnostic task.

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In practice, full Mueller imaging remains expensive to acquire. Estimating 16 matrix coefficients per pixel typically requires at least 16 intensity measurements, and classical systems often use more (> 32) for improved conditioning and calibration.⁵ Because many biomedical Mueller systems are time-sequential, this measurement burden translates into longer acquisition times, increased susceptibility to motion artefacts, and larger, more complex hardware. These limitations are particularly important in interventional settings, where motion, irregular tissue surfaces, blood contamination, and workflow constraints can all degrade measurement robustness and reduce clinical usability.⁶⁻⁹

These constraints motivate reduced Mueller acquisition strategies. Prior work has explored linear-only 3×3 acquisition for compact endoscopic and fiber-based systems, partial 3×4 acquisition using polarization-sensitive cameras, and task-driven partial polarimeter design in which only the most useful Mueller components are measured.¹⁰⁻¹⁵ Collectively, these studies show that reduced Mueller configurations serve as practically-relevant operating modes arising from real hardware and clinical constraints.

However, existing work is largely configuration-specific: individual reduced designs are typically introduced and validated in isolation, often on a single task or dataset. This makes it difficult to determine which reduced configurations offer the best trade-off between acquisition complexity and retained diagnostic utility. In this paper, we therefore treat reduced Mueller acquisition as a benchmarking problem. Rather than assuming one reduced scheme is canonical, we systematically compare multiple practically realistic configurations across biomedical tasks and datasets, and evaluate their speed-information-complexity trade-offs in relation to downstream diagnostic performance.

2. METHODOLOGY

2.1 Reduced Configurations

To assess the trade-off between polarimetric completeness and acquisition simplicity, we compare the full 4×4 Mueller matrix with several reduced configurations (Fig. 1). The full matrix serves as the reference setting, while the reduced variants are motivated either by realistic hardware simplifications or by controlled information ablations.

1. **Full 4×4 .** Reference configuration retaining all 16 Mueller elements, including both linear and circular terms.
2. **Upper-left 3×3 .** Retains only linear polarization terms and removes circular components. This is a common hardware-motivated reduction when generation and analysis are restricted to linear states.
3. **First three rows 3×4 .** Removes the circular output dimension while keeping all input states. It represents a simplified analyser and tests the effect of reduced output-side polarimetric information.
4. **First three columns 4×3 .** Removes the circular input polarization dimension while keeping all analysed outputs. It represents a simplified generator and enables comparison with 3×4 to assess whether reducing the PSG or PSA is more harmful.
5. **First row.** Minimal subset describing intensity response under varying incident polarization. This acts as a low-complexity baseline when no full output polarimetry is performed.
6. **First column.** Complementary minimal subset corresponding to a Stokes-like regime, where the emerging polarization response is measured under fixed illumination.
7. **Diagonal only.** Included as an information-ablation setting rather than a hardware-realistic design, testing whether task-relevant information is concentrated in the diagonal terms alone.

Together, these configurations span realistic and deliberate operating points, allowing us to quantify how diagnostic performance changes as measurement complexity is reduced. We note that these configurations specifically apply to this method of sequential data acquisition with bulk waveplates and polarizers, but similar considerations also apply to other methods of Mueller matrix acquisition.

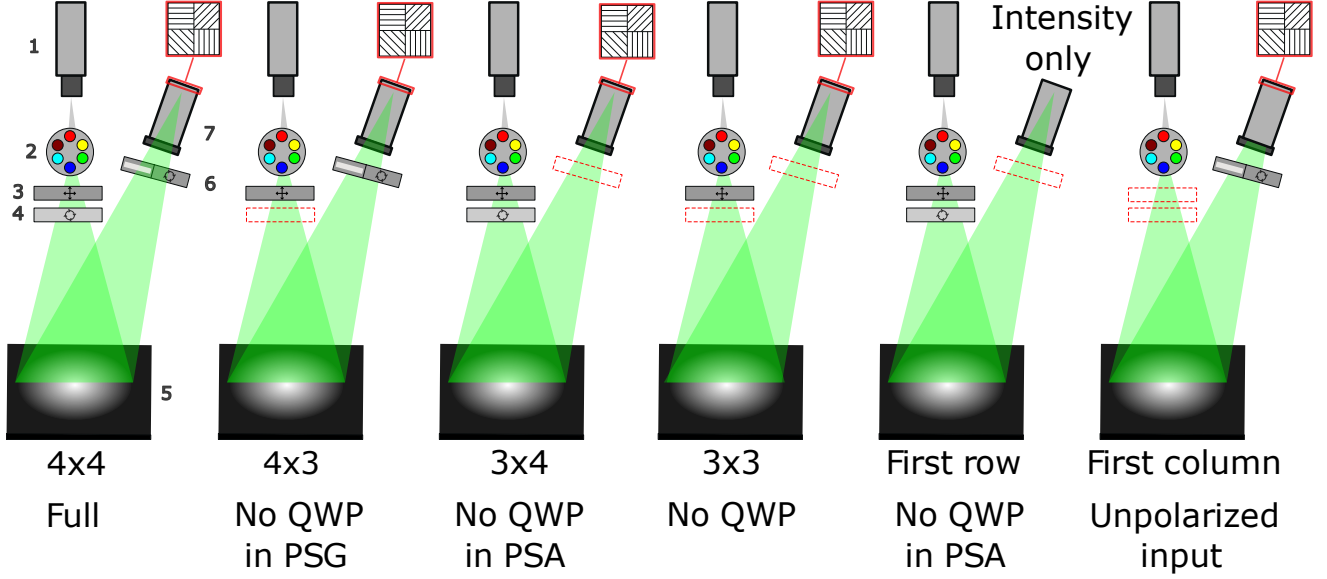


Figure 1. Reduced Mueller configurations considered in this work and representative hardware realizations. Components: (1) light source, (2) filter wheel, (3) linear polariser, (4) rotating mount with $\lambda/4$ retarder, (5) sample, (6) sliding filter mount with air or $\lambda/4$ retarder, and (7) polarization camera capturing linear states at 0° , 45° , 90° , and 135° .

2.2 Datasets

To evaluate reduced Mueller configurations, we benchmark across five biomedical datasets covering different tissues, acquisition modes, and prediction tasks (Table 1). These include the multispectral **PoLambRimetry** lamb-brain dataset, where we follow¹⁶ and collapse labels into white matter versus grey matter; the **ColoPola** colorectal dataset for normal versus cancer classification; the **Liver cancer dataset** containing histology ROIs from hepatocellular carcinoma (HCC) and intrahepatic cholangiocarcinoma (ICC), and surrounding normal tissue; the **Breast cancer dataset** with healthy, benign, and malignant categories; and the **Mice skin cancer dataset**, containing Mueller feature vectors of normal, papilloma (precancerous), and squamous cell carcinoma (SCC). These are provided as Mueller feature vectors rather than raw images.^{4,16–19}

Table 1. Datasets used in this study.

Dataset	Specimen / context	Data level	Labels / classes
PoLambRimetry ¹⁶	Lamb brain atlas	Multispectral Mueller-matrix images with ROI masks and labels	White matter vs grey matter
ColoPola ¹⁷	Human colorectal cancer	36 polarimetric frames per slice and/or derived Mueller matrix	Normal vs cancer
Liver cancer dataset ¹⁸	Human liver cancer	Mueller-matrix microscopy ROIs	HCC, ICC, and surrounding normal tissue
Breast cancer dataset ⁴	Human breast tissue	36 raw frames mapped to Mueller-matrix images	Healthy, benign, Stage 2, Stage 3
Mice skin cancer ¹⁹	Mouse skin cancer	Feature vectors from Mueller elements and optical parameters	Normal, papilloma, SCC

2.3 Methods

To evaluate each reduced Mueller configuration, we train a supervised decision-tree classifier (maximum depth = 10) on dataset-specific classification tasks. PoLambRimetry is treated as a binary grey matter versus white matter task, while ColoPola and the liver dataset are binary cancer classification tasks. To enable a consistent

cross-dataset binary comparison, the breast and mice skin datasets are also collapsed to normal versus cancer by merging the non-normal classes. Results for each dataset and configuration are reported in Table 2.

Each sample is represented by the available Mueller elements, with each reduced configuration corresponding to a predefined subset of the full 4×4 matrix. For image-based datasets, features are extracted at pixel level after normalising each Mueller element by m_{00} with the resulting features clipped to $[-1, 1]$. A fixed number of valid pixels are sampled uniformly from each image or acquisition, while rows in the mice skin dataset are treated directly as samples. To reduce class imbalance, the training split is randomly undersampled to the minority-class size.

Performance is reported under image-level evaluation. We use stratified image-level hold-out splits for most datasets, two-fold image-level cross-validation for the breast dataset, and leave-one-specimen-out evaluation for PoLambRimetry. Models are trained across multiple random seeds and the resulting performance is averaged.

3. RESULTS

Table 2. Overall classification accuracy for each reduced Mueller configuration across all datasets. The best results within each dataset are shown in bold, and the second best are underlined. Results are averaged over 20 runs with different seeds.

Configuration	Breast cancer	ColoPola	Liver	Mice skin cancer	PoLambRimetry
Full 4×4	<u>0.574</u>	0.691	0.610	0.684	0.878
Upper-left 3×3	0.572	0.637	0.533	0.712	0.871
4×3	0.574	0.643	0.566	0.721	0.874
3×4	0.575	<u>0.688</u>	<u>0.607</u>	<u>0.716</u>	<u>0.874</u>
First Column	0.459	0.624	0.519	0.707	0.630
First Row	0.472	0.625	0.523	0.677	0.659
Diagonal Only	0.482	0.620	0.500	0.686	0.870

From Table 2 we can see that utilising the full 4×4 Mueller matrix leads to the best accuracy for four of the five datasets (performance of 4×4 and 3×4 are about equal for the breast cancer dataset). This is expected as the full 4×4 isn't missing any elements or information. For the Mice skin cancer dataset, the 4×3 configuration achieves the best performance indicating that the last column actually hurts performance and leads to potential overfitting. For the breast cancer dataset, the best performing configuration is the 3×4 configuration. This configuration is also the second best performing for all the other datasets, suggesting that the best reduced configuration is the 3×4 configuration. This configuration has no circular component in the PSA which can greatly simplify the acquisition process and speed as a result.

4. CONCLUSION

For a variety of biomedical tasks, including human breast cancer, colorectal tissue, liver cancer, mice skin cancer and lamb brain, reduced Mueller matrix configurations were investigated to analyse the trade off between acquisition complexity and performance. The full 4×4 configuration performs best for most tasks as we would expect but given the acquisition complexity of full Mueller polarimetry, the 3×4 configuration serves as a viable alternative to full Mueller polarimetry. This configuration was the best performing for one task and the second best performing for all other tasks. Without the need for a circular analyser in the PSA, the acquisition time and hardware footprint could be reduced, simplifying clinical translation for Mueller polarimetry at a minimal reduction in performance. Further work to determine if the insights gathered from these datasets can translate into other biomedical domains is needed and experimental validation would also provide further support for reduced Mueller polarimeters.

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