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Lensless imaging systems: a technological and clinical review for automated disease identification

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ABSTRACT

We present an overview of previously reported Single Random Phase Encoding (SRPE) and Double Random Phase Encoding (DRPE) optical bio-sensing systems. In contrast to traditional imaging modalities that rely on lenses to capture and magnify subjects, SRPE and DRPE employ phase masks to modulate the light field emanating from an object. This modulation results in a pseudo-random optical signal to be received at the sensor, which is then classified by an appropriate classification algorithm. This lensless paradigm not only reduces the physical bulk and expense associated with optical components but provides wide field of view, and enhanced depth of field in comparison with lens-based imaging system. In biomedical imaging, the application of SPRE and DRPE systems has significant promise in the context of distinguishing between various types of red blood cells (RBCs) for disease diagnosis. Specifically, these imaging systems have demonstrated remarkable efficacy in identifying horse and cow RBCs, as well as differentiating between sickle cell-positive and negative RBCs with high accuracy and robustness to noise. The integration of Convolutional Neural Networks (CNNs), when trained directly on captured opto-biological signature (OBS) images show significant robustness to noise. Training a CNN on the Local Binary Patterns (LBP) of captured OBS images has shown not only improved classification performance but also maintained accuracy under conditions of significant data compression.

Keywords: Lensless imaging, Single Random Phase Encoding (SRPE), Double Random Phase Encoding (DRPE), Disease Identification, Sickle Cell, Convolutional Neural Networks, Cellular Biology, Diagnostic Applications

1. SYSTEM OVERVIEW

In this paper we overview previously reported work on Single Random Phase Encoding (SRPE) and Double Random Phase Encoding (DRPE) system for bio-sensing applications [1-6]. The concept of SRPE and DRPE arise from modulating phase by varying optical path length (OPL) across a surface [1-6]. The goal of these imaging schemas is to use a pseudo-random phase diffuser as an optical encoding element, with parameters of the scattering determined by exact specifications of the surface variations. The design of these systems uses a fully, or partially coherent source which is then propagated through a transmissive sample, to the diffuser(s), and the pseudo-random pattern is captured at the sensor. For cellular imaging, the captured pattern at the sensor is referred to as an opto-biological signature (OBS) [2-5]. We provide an example of an SRPE system for automated identification of sickle cell disease, in Fig. 1. [2].

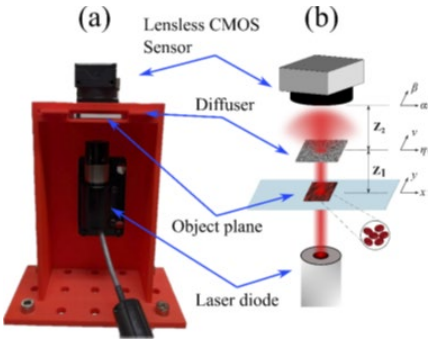

Figure 1: (a) 3D-printed experimental apparatus for single random phase encoding configuration, and (b) wave propagation starting from the laser diode, towards the object plane, through a diffuser, and finally a lensless CMOS detector with each respective coordinate system denoted [2].

Eliminating the lens from the imaging system and substituting it with a thin diffuser has substantially reduced the cost and size of optical designs, enhancing the feasibility and accessibility of sophisticated imaging technologies. This innovation in design not only yields a more compact and economical setup but also introduces significant robustness to critical sensor and design parameters such as pixel pitch and sensor size [1]. The theoretical advantages of SRPE systems are further evidenced by their superior performance in optical imaging tasks against lensed alternatives [5]. Notably, SPRE systems have demonstrated a marked improvement over Shearing Interferometry [5] in classification tasks, with initial research highlighting their efficacy when paired with random forest (RF) classifiers. It has also been shown directly training CNN on captured OBS images achieved 88.99% accuracy and 0.9649 Area Under the Curve (AUC) [3] in distinguishing between horse and cow RBCs. This approach also showcased a significant robustness to noise and obstructions compared to RF classifiers and emphasized the system's resilience. Building on the previous findings, Douglass et. al. (2022) demonstrated that a CNN trained on the local binary pattern (LBP) of OBS images could accurately classify sickle cell-positive and negative RBCs with 88.70% accuracy and a 0.9622 AUC [2], even under substantial data compression.

2. RESULTS AND DISCUSSION

The general workflow in SRPE and DRPE systems consists of three steps: (a) capturing a pseudorandom pattern through the lensless system, (b) extracting features (either handcrafted or through CNN) and (c) using the features for classification. Statistical feature extraction combined with a Random Forest (RF) classifier [4-5], or taking the LBP of a pseudorandom pattern prior to use in a CNN [2], have both been shown to be strong feature extraction methods. It has been shown that by using SPRE and DRPE systems we can obtain high performance results without a lens. This is accomplished by incorporating a random phase diffuser as an optical encoding element, which benefits from high spatial bandwidth [1-6], allows high amounts of compression [2], as well being robustness to noise [1,3], pixel pitch and sensor size [1]. These results collectively affirm that SPRE and DRPE systems, through the integration of a random phase diffuser as an optical encoding element, offer high spatial bandwidth, substantial data compression capabilities, and robustness to various imaging challenges such as noise, pixel pitch, and sensor size variations.

3. CONCLUSIONS

In summary, we have overviewed our previously reported works on SRPE and DRPE for cellular classification task [1-6]. These systems utilize pseudo-random phase masks for optical signal modulation. It has been shown that SRPE with CNN outperform the Shearing Interferometry for RBCs classification [3], is able to maintain classification accuracy under significant dimensionality reduction [2], and is robust to the physical parameters (pixel size, number of pixel, etc.) of imaging system [1].

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