Holographic photonic neuron

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Keywords: neuromorphic photonics, optical correlator, optical angular momentum

Abstract
The promise of artificial intelligence (AI) to process complex datasets has brought about innovative computing paradigms. While recent developments in quantum-photonic computing have reached significant feats, mimicking our brain’s ability to recognize images are poorly integrated in these ventures. Here, I incorporate orbital angular momentum (OAM) states in a classical Vander Lugt optical correlator to create the holographic photonic neuron (HoloPheuron). The HoloPheuron can memorize an array of matched filters in a single phase-hologram, which is derived by linking OAM states with elements in the array. Successful correlation is independent of intensity and yields photons with OAM states of $l\hbar$, which can be used as a transmission protocol or qudits for quantum computing. The unique OAM identifier establishes the HoloPheuron as a fundamental AI device for pattern recognition that can be scaled and integrated with other computing platforms to build-up a robust neuromorphic quantum-photonic processor.

1. Introduction
The challenge to process large and complex datasets has motivated the quest for new computing paradigms. Silicon-based neuromorphic or biologically inspired artificial intelligence (AI) technologies allow for more effective deep learning algorithms capable of handling complex and large datasets [1–3]. However, neuromorphic photonics have now emerged as a promising option [4–6]. A neuromorphic silicon-photonic processor has been shown to solve the Lorenz attractor differential equation [7]. While the computing speed has improved, storing and readout of optical memories have difficulty coping up with clock speeds in gigahertz frequencies [8–10]. The bottleneck also occurs when transferring information data from one computing platform to the other [11], which hinders scalability and integration.

Yet processing clock speeds may not be all that matter. There is a large disparity when comparing AI technologies with how our brain works. Apart from the large gap in energy consumption, the temporal dynamics of synaptic processes in our brain operate in kilohertz range and still outperform computing functions, such as machine vision. With our current understanding of memory formation [12] and vision processing [13, 14] in the brain, our own experiences can tell that while we can instantaneously view and process highly resolved details of visual scenes, some of these details are not fully stored in our brain. Processing of visual data are concatenated into pertinent information and stored as synaptic strengths in networks of neurons in different regions of our brain. When recalling our memories, our brain offers seamless transfer of information data from different brain regions making it possible to recognize patterns in a probabilistic manner. Hence, if we were to get inspiration from this model, building an intelligent neuromorphic computer implies a system with high resolution instantaneous processing, concatenated storage of pertinent information, distributed processing and the ability to seamlessly integrate and transmit information within multiple platforms such as deterministic with probabilistic computing operations.

There has been significant work on optical implementations of machine vision systems based on the Vander Lugt optical correlator [15, 16]. The correlator epitomizes classical optical computing that measures the
similarity between two patterns. The optical correlator is implemented via a 4f lens setup where the multiplication of a pre-determined matched filter and the Fourier transform of the input pattern is performed at the Fourier plane [17]. Matched filters in a Vander Lugt correlator represent memory storage that could provide instantaneous readout and processing at the speed of light. Matched filters can also be applied using only its phase [18] and can be multiplexed and stored as phase holograms [19–22].

Over 50 years have passed and the Vander Lugt correlator remains an effective tool for pattern recognition problems such alignment of deoxyribonucleic acid (DNA) sequences [23] or counting k-mers substrings in a DNA string [24]. Pattern recognition can also be achieved via optical artificial neural networks (ANNs) [25, 26]. Diffractive deep neural networks (D2NNs) use multiple holographic layers, where each point in the hologram acts as a neuron with a complex-valued transmission coefficient [27]. To arrive at a desired output, Fresnel light propagation through the layers intricately incorporates lens functions in the holograms during learning. The Vander Lugt correlator, on the other hand, employs classical optical computing, where Fourier transform operations carried out by lenses effectively set up light paths like a fully connected ANN. One could therefore argue that the Vander Lugt correlator is a three-layer ANN, where the 1st and 3rd layers take the form of diffractive lenses. Training such three-layer ANN entails finding the appropriate complex-valued transmission of the 2nd layer, which is essentially the matched filter. And while D2NNs can use more than 3 layers, probabilistic pattern recognition is still performed via classical computing operations.

Despite these recent advances in neuromorphic [6] and optical AI technologies [28], probabilistic classical optical computing operations are not yet fully integrated with quantum computing. While a quantum optical neural network has been proposed to perform a number of quantum information processing tasks [29], pattern recognition is not among those tasks. In an effort to demonstrate a quantum-based Vander Lugt correlator, Qiu et al [30] used a pump beam with a Laguerre–Gaussian (LG) mode in a ghost imaging setup. To perform quantum correlation, the interaction between the spatial frequency information of the object and the filter is performed via down-converted photon pairs at the Fourier domain. The orbital angular momentum (OAM) based quantum Vander Lugt correlator, however, was only demonstrated to perform vortex mapping and identification [30].

Here, I propose to integrate classical optical computing with quantum computing by incorporating OAM states via LG laser modes [31] in a classical Vander Lugt correlator. I refer this technique as the holographic photonic neuron or HoloPheuron. I show both numerical and proof-of-principle benchtop experiments demonstrating the efficacy of using OAM-states as correlation metric. I also show the efficacy and limitations of the HoloPheuron to perform image and pattern recognition. Aside from circumventing the dependence on intensity, using OAM states as correlation metric can link macroscopic classical optics with quantum effects. OAM-states have been demonstrated to be effective transmission protocol for quantum communications [32–35], photonic qubits in quantum computers [36] and as multi-level qudits in quantum information protocols [37]. Hence, integrating classical optical computing with quantum techniques could potentially bring us closer to realizing a robust quantum-based machine vision processor.

2. Methodology

2.1. Holographic photonic neuron

The HoloPheuron is implemented via a 4f lens setup with a multiplexed matched filter at the Fourier plane (figure 1(a)). The multiplexed matched filter contains information from a training set consisting of an array of visual data. The matched filter of an ith element in an array of N elements is related to the two-dimensional (2D) Fourier transform of an input pattern \( a_i(x, y) \) given by,

\[
A_i(u, v) = \mathcal{F} \{ a_i(x, y) \}
\]

where \( (x, y) \) are spatial coordinates at the input plane and \( (u, v) \) are spatial frequency coordinates at the Fourier plane. Training the HoloPheuron links spatially distinct, non-overlapping, LG modes to individual elements in the array via a carrier phase function, \( \psi_i(u, v) \), given by

\[
\psi_i(u, v) = 2\pi (m \cdot u + n \cdot v) + l\varphi
\]

where \( \varphi = \arctan \{v/u\} \) is the azimuthal angle around the optical axis, \( l \) is the topological charge of an LG beam, and \( (m, n) \) are the spatial locations of the correlation peaks at the output. By linear superposition \([19, 20]\), the resultant field of \( N \) matched filters, is given by

\[
W(u, v) = \sum_{i=0}^{N} \exp \left( j \psi_i(u, v) - \arg \{ A_i(u, v) \} \right)
\]
Figure 1. (a) The holographic photonic neuron (HoloPheuron) with a phase-only matched filter that yields photons with OAM states as unique identifier. (b) Illustration of operation where an input pattern, $a_i(x,y)$, whose Fourier transform, $A_i(u,v)$, is linked with a carrier phase function, $\psi_i(u,v)$, and linearly combined with other patterns to form $W(u,v)$. The carrier phase function can be encoded with an optical vortex to produce output photons with OAM of topological charge $l$. The top row shows an input pattern ‘a’ is encoded with $l=0$, which yields a Gaussian correlation peak, while the bottom row shows an input pattern ‘b’ is encoded with $l=+1$ producing an optical vortex.

whose 2D phase profile $\arg\{W(u,v)\}$ is the hologram containing pertinent information of $a_i(x,y)$. On read-out, the output field of the HoloPheuron is given by

$$o_i(x',y') = F^{-1}\{\exp(\arg\{W(u,v)\}) \cdot A_i(u,v)\}$$

Figure 1(b), graphically describes the process for a training set of $N=2$ patterns (‘a’ and ‘b’). The carrier phase functions, $\psi_i(u,v)$, with OAM states $l=0$ and $l=+1$ (with $m=n=constant$) are linked to patterns ‘a’ and ‘b’, respectively. Consequently, $W(u,v)$ is derived for $N=2$ matched filters. The positions $(m,n)$ of the correlation peaks at the output plane can be set arbitrarily, which will depend on the succeeding stage of computing or transmission such as an optical fibre bundle or a multi-channel detector.

2.2. Numerical simulation

The HoloPheuron can be simulated using a program implemented in LabView (National Instruments). I used 36 alphanumeric patterns of different fonts and 36 face photographs from the Bainbridge database [38, 39]. The alphanumeric and face photographs were first converted into grayscale and centered in an $M \times M$ pixel array (where $M=1000$) prior to using them as input patterns ($a_i(x,y)$) onto a 2D Fourier transform (see equation (1)). The 2D input patterns are set as amplitude modulated patterns with constant phase, while the phase of the output of the Fourier transform is used as the matched filter. Carrier phase functions were derived using equation (2), where the indices $m$ and $n$ can be set to identify specific locations of the correlation peak at the output plane, while $l$ sets the OAM state. In the program, $m$ and $n$ scale the $x$- and $y$-prism functions, respectively, to shift the correlation peaks along transverse direction at the output plane, while $l$ scales a helical phase around the optical axis or along the azimuthal angle $\phi$. To derive the $N$-multiplexed matched filters, equation (3) is implemented via for-loop to sum the field containing the subtracted phases of the matched filter from the carrier phase function.

To implement the cross-correlation of the input patterns with the $N$-multiplexed matched filters ($W(u,v)$), the optical system was simulated to use a finite operating region around the optical axis. Hence, only a portion
of the \( M \times M \) array is used, which is truncated by a circular aperture of radius set to \( M/4 \). The relatively small aperture with respect to \( M \) results in a ‘diffraction-limited’ transverse Airy pattern as correlation peaks (when \( l = 0 \)), which effectively simulates experimental conditions \([40, 41]\). Moreover, since only the phase of \( W(u, v) \) is required, the amplitude was set to unity and multiplied with the field of the Fourier transform of the input pattern. The output of the HoloPheuron takes the inverse Fourier transform after the multiplication of the fields. The intensity and phase distributions of the output field characterize the output of the HoloPheuron for different input patterns and OAM conditions.

2.3. Experiment

The experimental setup makes use of a phase-only spatial light modulator (SLM) (Hamamatsu LCOS X10468-01 800 \( \times \) 600) and a green laser (532 nm Finesse, Laser Quantum). Two convex lenses (\( f = 200 \) mm) build up a 4f imaging setup where the SLM is placed at the Fourier plane. To ensure proper alignment and scaling of the calculated spectral components with experimental conditions at the Fourier plane, the system was first calibrated using the generalized phase contrast (GPC) method \([42]\).

To align the system using the GPC method, a circular aperture was placed at the input and a circular phase filter was encoded on the SLM to shift the focused zero-order beam by \( \pi \) (supplementary figure 1(a) (https://stacks.iop.org/NCE/1/024009/mmedia)). Since the diameter of the input aperture sets the intensity distribution of the zero-order beam, its interaction with a circular phase filter sets a characteristic intensity distribution at the output of the 4f imaging setup \([43, 44]\). When aligned properly, the filter changes the intensity distribution at the output of the 4f imaging setup depending on the amount of light shifted by the filter (supplementary figure 1(b) bottom). When the SLM is off, the camera acquires the image of the input, and for this case, it shows an image of the laser-illuminated input aperture (supplementary figure 1(b) top).

I then used the GPC method to calibrate the spectral resolution necessary for accurate encoding of the calculated matched filters \( \{ W(u, v) \} \) onto the SLM. To calibrate, I varied the matrix size \( M \) to yield a similar image as the experiment. I used the image of the aperture as input and embedded it at the center of an \( M \times M \) array (supplementary figure 1(b) top). I then simulated the GPC method via a pair of \( M \times M \) 2D Fourier transforms with variable \( M \) and using the same filter size as encoded onto the SLM for alignment. The image of the aperture was kept constant as \( M \) was varied. The intensity distribution at the center of the Fourier plane is influenced by the size of the aperture (image) with respect to the size of the array (supplementary figure 1(c)). Using \( M = 1500 \) yields a closest image with the GPC experiment (supplementary figure 1(b) bottom) and was hence used to calculate for \( W(u, v) \) (supplementary figure 1(d)).

To demonstrate the performance of the HoloPheuron, the input patterns where projected by placing a transparency printed with alphanumeric patterns. To calculate the \( W(u, v) \), the input patterns were first imaged using a camera. The face photographs were converted to grayscale and embedded and centered on an \( M \times M \) array, where \( M = 1500 \). During training, certain patterns were selected to be part of the training set \( W(u, v) \) and 2D Fourier transforms of their respective \( M \times M \) arrays were calculated and combined via linear combination as described in equation (3). The resulting \( \{ W(u, v) \} \) is cropped and encoded onto the SLM with 600 \( \times \) 600 phase-shifting pixels (supplementary figure 1(a)). When the SLM is turned off, it functions as a mirror and the output registers an image of the input pattern. When the SLM is turned on and encoded with \( \{ W(u, v) \} \), the output registers a correlation peak when the input pattern is part of the training set. Since the calibration procedure was only an approximation, the value of \( M \) was later fine-tuned (\( M = 1480 \)) to obtain optimum correlation peaks.

3. Results

3.1. Encoding OAM states

The performance of the HoloPheuron is verified via numerical simulations and a benchtop experimental setup. Figure 2(a) plots the correlation peak intensity resulting from the autocorrelation of the pattern ‘a’ with OAM states from \( l = -1 \) to \( l = +6 \). The autocorrelation of an input pattern is performed when \( W(u, v) \) is derived with the matched filter of the same pattern (\( N = 1 \)). The correlation peak position is set at the optical axis (\( m = n = 0 \)) and the intensity is normalized to the maximum intensity when \( l = 0 \). The intensity along the vortex is not constant and the three points plotted per OAM state are the maximum, minimum and average intensities. The zoomed-in images of the vortices and their corresponding phase patterns are shown. For reference, the amount of zoom can be compared with the conjugate image of the input pattern ‘a’ when \( W(u, v) = 1 \). While the maximum intensity of the correlation peak is drastically reduced to noise level at high \( l \), the phase-singularity at the output can still be detected.

Figure 2(b) shows the correlation of letters ‘a’ to ‘e’ (Bradley Hand font) using a \( W(u, v) \) derived with \( N = 5 \) matched filters (supplementary video 1). The intensity and phase distributions at the output for OAM states from \( l = -2 \) to \( l = +2 \) are shown. The spatial positions of the correlation peaks (red circles) are arranged...
Figure 2. (a) The correlation peak intensity resulting from the autocorrelation of a pattern ‘a’ encoded with OAM states from \( l = +1 \) to \( l = +6 \). The 2D intensity and phase distributions are shown per \( l \) setting. Red arrows indicate the direction of helicity with phase values from \(-\pi\) to \(+\pi\). (b) The output intensity and phase distributions resulting from the cross-correlation of patterns ‘a’ to ‘e’ encoded with OAM from \( l = -2 \) to \( l = +2 \), respectively.

Symmetrically along the optical axis \((m = n = 0)\) where the correlation peak for pattern ‘c’ \((l = 0)\) is located. The phase-singularities can be discerned from the phase distributions, which can be detected using spiral imaging [45], quantum-based vortex mapping [30, 46] or via machine learning recognition [47].

The experimental demonstration is performed using a green laser and a phase-only SLM (figure 3(a)). The input patterns are printed on a transparency and imaged through the 4f imaging setup where the SLM is placed at the Fourier plane and a camera at the output. Prior to performing optical correlation, \( W(u, v) \) was derived with no OAM \((l = 0)\) by calculating the inverse Fourier transform of the image of the input pattern ‘a’ (Arial font). The image of the input pattern is acquired by turning the SLM off, which effectively sets \( W(u, v) = 1 \) (figure 3(b)). When the SLM is turned on and encoded with \{W(u, v)\}, the autocorrelation of the input pattern ‘a’ yields a Gaussian correlation peak \((l = 0)\) (figure 3(d)). Next, I calculated \( W(u, v) \) for \( N = 1 \) but with different OAM states from \( l = -3 \) to \( l = +3 \). Figure 3(e) shows optical vortices corresponding to the OAM states resulting from the autocorrelation of the pattern ‘a’. A \( W(u, v) \) with \( N = 2 \) matches filters for patterns ‘a’ and ‘b’ can also be calculated with different OAM states. Figure 3(f) shows the correlation peaks for \( l = 0 \), while figure 3(g) shows the output for two different OAM states of \( l = -1 \) and \( l = +1 \) linked to letters ‘a’ and ‘b’, respectively.

3.2. Intensity and noise dependence

The OAM at the output is independent of the performance of the HoloPheuron. Hence, we can assess the correlation efficacy using \( l = 0 \), where it represents a Vander Lugt correlator with multiplexed phase-only matched filters. Figure 4(a) is data from the experiment using a training set with \( N = 2 \) patterns, ‘a’ and ‘b’. Setting the input pattern to either ‘a’ or ‘b’ results in a correlation peak (yellow arrows). Since the input patterns are switched and moved along the \( x \)-axis, the correlation peaks are assigned with non-overlapping \( y \)-axis positions. On the other hand, input patterns ‘c’ and ‘d’, which are not within the training set, did not yield correlation peaks (supplementary video 2).

Increasing the number of multiplexed matched filters yields lower correlation peak intensities. Using numerical simulation, complex patterns from 36 face photographs [38] and 36 alphanumeric characters were used to assess the correlation and discrimination efficacy. Color photographs were first converted to grayscale before performing correlation. For easier analysis, the positions of the correlation peaks at the output are arranged in a square array (e.g. \( N = 4 = 2 \times 2, N = 9 = 3 \times 3 \), up to \( N = 36 = 6 \times 6 \)). Figure 4(b) shows correlation results using a \( W(u, v) \) with \( N = 9 \) matched filters for a training set containing normal contrast (NC) face photographs (supplementary video 3), while figure 4(c) shows results for \( N = 16 \) alphanumeric characters (Bradley Hand font) (supplementary video 4). As with figure 4(a), the top two patterns in figures 4(b) and (c) are patterns within the training set yielding correlation peaks (yellow arrows), while the bottom patterns are not. Note that in figures 4(b) and (c), similarities in the NC face photographs...
Figure 3. (a) Optical setup of the HoloPheuron where \( \arg \{ W(u,v) \} \) is encoded on a phase-only SLM located at the Fourier plane. (b) Output image of the input pattern when \( W(u,v) = 1 \) or when the SLM is turned off. (c) Representative phase hologram \( \arg \{ W(u,v) \} \) derived with \( N = 1 \) and no OAM \( (l = 0) \). (d) The autocorrelation of 'a' yields a Gaussian correlation peak. (e) The autocorrelation of 'a' yields an output where the OAM is varied from \( l = -3 \) to \( l = +3 \). The correlation of letters 'a' and 'b' using a training set with \( N = 2 \) matched filters and with OAM states (f) \( l = 0 \) and (g) \( l = -1 \) for 'a' and \( l = +1 \) for 'b'.

(NC#15 and NC#01) and patterns 'm' and 'w' yield false positives (red circles). I will discuss this issue in the next section.

On average, the correlation peak intensities for face photographs and alphanumeric characters follow a \( 1/N \) profile as expected from the conservation of energy (figure 4(d)). The linear combination of \( N \) matched filters is equivalent to producing holographically projected multiple foci from a single laser [48]. However, the output of the HoloPheuron produces only a single correlation peak, which projects the rest of the photons as background noise. Hence, it is important to consider the signal-to-noise ratio (SNR) of the correlation peaks when detecting peak intensities for \( l = 0 \).

The SNR is determined by the ratio of the correlation peak intensity over the peak-to-peak noise (supplementary figure 2). Figure 4(e) plots the SNR (left axis, marked traces) for alphanumeric patterns (red trace) and face photographs (blue trace) as a function \( N \). There is a stark difference between high contrast (HC) binary patterns such as alphanumeric characters (red dashed trace) over complex multi-level images of faces (blue dashed trace). Compared to face photographs, the SNR for alphanumeric characters is relatively high for \( N < 9 \), but drastically degrades at higher \( N \). The blue shaded area indicates when the correlation peak is less than the noise. Figure 4(e) also plots the success rate for identifying correlation peaks (right axis, unmarked traces) for alphanumeric patterns (red trace) and face photographs (blue trace). The success rate is the percentage ratio of the number of correlation peaks with \( SNR > 1 \). For \( N = 9 \), the success rate for identifying faces is still 100% (blue solid trace), while alphanumeric characters (red solid trace) have large deviations with success rate of 77.8%.

3.3. False negatives and false positives

Large deviations in correlation peak intensities yield false negatives, where the peak intensity is below the background noise. Figure 5(a) shows indistinguishable peaks for patterns 'i' and 'l' using a \( W(u,v) \) with \( N = 16 \) alphanumeric patterns (Bradley Hand font). High correlation peaks for 'i' and 'k' with intensity profile (gray traces) along the \( x' \)-axis are shown for comparison. On the other hand, the intensity profiles show that the correlation peaks for 'i' (blue trace) and 'l' (red trace) are below the background noise. However, when the matched filters are linked with OAM state \( l = +1 \), the output yields a helical phase profile at the location of the correlation peak. Hence, the phase singularities where \( l \neq 0 \) can still be detected even when the correlation peak with \( l = 0 \) is below the noise level.
Similarities in the patterns yield a secondary correlation peak, which can reduce the efficacy of identification. Figure 5(b) shows secondary peaks resulting from the correlation of patterns ‘c’ and ‘e’ using \( W(u, v) \) with \( N = 9 \) alphanumeric characters (Times New Roman font). Moreover, using a carrier phase function with OAM states \( l = +1 \) and \( l = -1 \) for patterns ‘c’ and ‘e’, respectively, also returns opposing helical phase singularities in both 1st and 2nd correlation peaks, respectively. Hence, detecting phase singularities to differentiate the two characters will not be effective. While the true positive peak is higher than the 2nd peak, these issues are common problems in machine vision [49]. Approaches based on convolutional neural networks (CNNs) to decompose the spatial frequencies of the pattern into sub-groups can be used to optimize discrimination between similar patterns.

The correlation peaks \( (l = 0) \) for complex multi-level patterns (face photographs) also yield false positives. Figure 6 shows patterns with similar features resulting in secondary peaks with lower intensities. The training set contains \( N = 9 \) matched filters for patterns NC#00 to NC#08 (supplementary figure 3(a)). Figure 6(a) shows an example where NC#01 sets a correlation peak (1st peak) at the top row, while NC#08 yields its 1st peak at the bottom right. However, changing the grayscale of the face photographs to HC improves the correlation results (figure 6(b), supplementary figure 3(b)).

Improving the contrast can also solve false positives for input patterns outside the training set. Figure 6(c) shows an example where a false positive occurs with an input pattern NC#10, which shows a correlation peak for NC#03. Changing the contrast effectively discriminates and reduces the correlation peak when the HoloPheuron is presented with HC#10 (figure 6(d), supplementary figure 3(b)). The summary of changes in correlation peak intensity for true and false positives is shown in figure 6(e), which includes results presented in supplementary figure 3. Figure 6(h) shows the SNR (left y-axis, marked traces) and identification success rate (right y-axis, solid unmarked traces) for NC (blue trace) and HC (red trace) patterns as a function of \( N \) matched filters.

### 3.4. Spatial frequency components

Differences in performance between NC and HC patterns are due to the spectral components of the edges in black and white or HC patterns, which produce distinct mid-frequency phase signatures away from the optical axis. On the other hand, multi-level amplitude modulated patterns (e.g. grayscale photographs) produce low-frequency phase signatures close to the optical axis. Since the small area close to the optical axis can only multiplex a finite number of matched filters, there is a high probability for cross talk between signatures from different images resulting in secondary peaks. To investigate this effect, I probed how the spatial frequency representation influences the correlation peak.
Figure 5. False negatives and false positives. (a) Using $W(u,v)$ with $N = 16$ matched filters and $l = 0$, yields low correlation peak intensities (red and blue circles). High correlation peak intensities (gray circles) for ‘j’ and ‘k’ are shown for comparison. The intensity profiles along the $x'$-axis are shown for patterns ‘i’ (red) and ‘l’ (blue) as well as ‘j’ and ‘k’ (gray). Using $l = \pm 1$ for both patterns yield phase singularities (yellow circles) with zoomed inphase distributions with red arrows indicating the direction of helicity from $-\pi$ to $+\pi$. (b) Using $W(u,v)$ with $N = 9$ and $l = 0$ yields higher correlation peak intensities but similarities of features for patterns produce secondary peaks. Encoding OAM states with opposing charges also yield phase singularities at the secondary peaks.

Figure 7(a) plots the correlation peak intensity for a training set of $N = 2$ matched filters as a function of the radius ($f_r$) of the active area of the hologram. The active area sets the phase hologram equal to $\arg \{W(u,v)\}$, when $\sqrt{u^2 + v^2} < f_r$ and zero when $\sqrt{u^2 + v^2} > f_r$ (supplementary figure 4(a)). Moreover, the finite dimensions of a holographic recording device, such as an SLM, sets a limiting amplitude at the Fourier plane where it is fully transmissive within a square aperture of side length $L$ (supplementary figure 4(b)). Each data point in figure 7(a) is an average of the correlation peak intensities of the patterns within the training set. A linear increase in correlation peak intensity occurs when $f_r$ exceeds a critical frequency, $f_c$. And as expected, when $f_r > L/2$, the maximum correlation peak intensity is constant since light is only transmitted within the aperture of the SLM.

The finite transmission aperture of the SLM at the Fourier plane sets the maximum correlation peak intensity as well as the intensity distribution of the correlation peak at the output. The aperture effectively sets the numerical aperture of the optical system, where a small aperture results in a broader point spread function of the correlation peaks (figure 7(b)). It also affects the phase singularity when $l \neq 0$. Figure 7(c) shows the intensity and phase distribution for $l = \pm 2$ for different aperture diameters. Phase discontinuities for $l \neq 0$ remain constant and independent of the system’s numerical aperture.

The storage of spatial frequency information differentiates the correlation between NC and HC patterns. Figure 7(d) plots the output peak intensity as a function of $f_r$ for a training set with $N = 9$ matched filters. Representative output intensity distributions are shown for three types of inputs: HC (red), NC (blue) and alphanumeric (green) patterns. Note that each pattern type has their respective $W(u,v)$’s calculated. At $f_r = 0$, the hologram at the Fourier plane is fully transmissive with no spatial phase modulaton and the output yields a conjugate image of the input. When $f_r = f_c$, the output produces an inverse intensity image, which sets the measured correlation peak intensity at minimum. From the plot, we can deduce that for $f_r < f_c$, the spatial frequency information stored in $\arg \{W(u,v)\}$ has minimal effect to produce an effective correlation peak. However, when $f_r > f_c$, a linear increase in the peak intensity indicates that pertinent spatial frequency information stored in the hologram results in effective correlation.

Plotting the effect of $f_r$ on the correlation peak determines the pertinent spatial frequency information necessary to be stored in the hologram. Moreover, differences in $f_c$’s indicate that the stored spatial frequency information within $W(u,v)$ is highly dependent on the pattern type. NC patterns yield an $f_c$ closest to the optical axis, while alphanumeric patterns exhibit the highest $f_c$ among the three image types. HC patterns result in a slightly higher $f_c$ (compared to NC) thereby increasing the active area of stored phase signatures.
Hence, increasing the contrast of the visual data allows for an increased storage of relevant phase signatures for effective identification and discrimination.

3.5. Activation function
The activation function of the HoloPheuron can be probed by plotting the correlation peak intensity as a function of the total number of phase-shifting pixels within the active area of the hologram. Figure 7(e) plots the activation function of the HoloPheuron for different $N$ and with fixed SLM size of $L = 0.4 M$. An OFF-state occurs when the number of active hologram pixels is not enough to provide effective correlation, which occurs when $f_r < f_c$. As the number of hologram pixels is increased ($f_r > f_c$), the HoloPheuron turns to ON-state and projects a correlation peak. Since the finite number of pixels in the hologram limits the correlation peak intensity, the peak remains constant when $f_r$ exceeds the total area of the SLM contained within $L \times L$.

From the plot of the correlation peak versus the number of pixels, the activation function of the HoloPheuron can be fitted with a sigmoidal function (figure 7(e)).

4. Discussion
The HoloPheuron operates as a Vander Lugt optical correlator where the matched filters containing the spatial frequency information of visual data is stored as a phase hologram. By linking the matched filters with OAM states and multiplexing them into a single hologram, the HoloPheuron can identify patterns within the training set and discriminate those outside. The HoloPheuron sets output photons carrying OAM states, which can be used as transmission protocol or multi-level qudits for quantum computing.

Linking the OAM with the output photons can provide effective correlation that is independent of light intensity and can hence circumvent false negatives. However, the HoloPheuron suffers from false positives, which is a common problem in machine vision. Improving the contrast of complex multi-level (grayscale) patterns such as face photographs can improve the performance. However, the problem still exists for simple yet HC patterns (e.g. alphanumeric). Similarities in the patterns produce unwanted correlation peaks that reduce the efficacy of the HoloPheuron. In practice, multiplexed matched filters may not store information from entire images (faces or alphanumeric) but decomposed fragments, where the output represents only certain characteristic features. By identifying the critical frequency ($f_c$) of image types, fragments of pertinent spatial frequency information can be stored appropriately onto the hologram. Within a tolerable output noise
level, concatenated storage is possible where the hologram can be encoded in a smaller array of phase-shifting pixels provided the encoded radial frequencies exceed $f_c$.

Alternative machine vision approaches use deep-learning with artificial feed-forward ANNs [27, 28, 50]. ANNs are used within a CNN, which operate by decoding the spatial dependencies of pixel information in a pattern. Prior to feeding the information to a feed-forward ANN, input patterns undergo a convolution with pre-set filters to find dependencies between neighboring pixels and spatial frequency information of the pattern. The convolution layer effectively finds the necessary spatial frequency signatures, which are fed into the ANN for learning and eventually identification or classification. Likewise, the HoloPheuron could represent different stages of the CNN where the spatial frequencies of the input pattern are decomposed [51, 52]. False-positives may occur in earlier stages but will eventually be decided upon by further processing. The potential for an all-optical neuromorphic implementation of the CNN can be realized using OAM states as information carriers between interconnected network of HoloPheurons.

5. Conclusion

Classical optical correlators represent certain functions in our brain, specifically in neuronal circuits responsible for our vision and our ability to recognize and classify patterns. Oftentimes, we need visual representation of the complex problem to analyze and solve accordingly. Our vision-aided analytical skills and creativity, such as making sense of mathematical equations, graphs and puzzles or writing/reading musical notes, are common examples of human intelligence that has not yet been accurately replicated by machines. Hence, building an intelligent computer requires such skills to be integrated with deterministic computing platforms.

The HoloPheuron could be used as a visual processing unit. We can take our queue from the neural basis of the mammalian visual system. The Hubel and Wiesel [13] model of vision is hierarchical where complex visual responses build up from simpler processes from different neurons. Moreover, multiple neurons in the visual cortex respond to certain spatial frequencies of patterns [14]. The visual cortex consists of channels of neurons
that are tuned to different spatial frequencies, and their collective response results in the visual perception of patterns. Similarly, interconnecting multiple HoloPheurons with concatenated spatial frequency information is necessary to provide more accurate identification of the input patterns. And by using OAM states as carriers of information between HoloPheurons and other neuromorphic paradigms, we can potentially build-up a robust and effective machine vision processor.

Acknowledgments

I thank Hans-A Bacher, Mary Jacqueline Romero, Dragomir Neshev and Timothy Senden for their insights and helpful discussions.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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