Research Article

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Toward spectrometerless instant Raman identification with tailored metasurfaces-powered guided-mode resonances (GMR) filters

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Abstract: Raman identification is an instrumental tool with a broad range of applications, yet current spectroscopy approaches fall short in facilitating practical and scalable Raman identification platforms. In this work, we introduce a spectrometerless Raman identification approach that utilizes guided-mode resonance filters. Unlike arrayed narrowband-filters spectrometer, we tailor the transmission characteristics of each filter to match the Raman signature of a given target. Hence, instantaneous Raman identification could be directly achieved at the hardware level with no spectral data post-processing. The filters consist of a metasurface grating encapsulated between two identical distributed Bragg reflectors and are characterized by transmission peaks line-widths narrower than 0.01 nm and transmission efficiency exceeding 98%. We develop a rigorous design methodology to customize the filters' characteristics such that the maximum optical transmission through a given filter is only attained when exposed to the Raman scattering from its matched target. To illustrate the potential of our approach, we theoretically investigate the identification of four different saccharides as well as the classification of two antibiotic-susceptible and resistant strains of *Staphylococcus aureus*. We show that our proposed approach can accurately identify these targets. Our work lays the foundation for a new-generation of scalable, compact, and cost-effective instant Raman identification platforms that can be adopted in countless

applications from wearables and point-of-care diagnostics to in-line quality control in food and pharmaceutical industries.

Keywords: GMR; high-Q filters; Raman identification; spectrometerless.

1 Introduction

Since the first observation of Raman scattering in 1928 [1], it has emerged as one of the most intriguing light–matter interaction phenomena. This nonelastic photon scattering process gives rise to characteristic optical signatures that can directly probe the composition and the structure of the scatterer even at the single molecular level [2–8]. This incredible sensitivity rendered Raman spectroscopy a powerful chemical and molecular identification tool [9] with a wide range of applications from real-time biological imaging [10–15] and cellular identification [16–18] to drug quality control [19–22] and art restoration [23–25].

Despite its great promise, wide adoption of Raman imaging and identification has been hindered by a few technical limitations. One of these major milestones is associated with the hardware required to achieve sufficient spectral resolution. Accurate Raman identification requires high-resolution spectral data to resolve the unique Raman features of the targets. Typical Raman spectrometers are bulky, often expensive, devices with large footprints that require frequent calibration and realignment. Therefore, several approaches have been introduced to provide compact and cost-effective spectrometers. This includes folded metasurfaces [26], micro-donut resonators [27], micro-ring resonators with a diffraction grating [28], photonic crystal cavity arrays [29, 30], and disordered photonic structures [31] among others. Unfortunately, these techniques remain inadequate for Raman identification approaches due to either limited resolution

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(>1 nm), narrow operation bandwidth, or inefficient on-chip coupling.

Another promising approach for compact spectrometers utilizes on-chip narrow-band optical filters integrated on photodetector arrays [32–41]. This technique allows each filter to transmit only a certain spectral band to a specific spot on the detector array. Thus, spectral measurements can be performed using an array of optical filters with transmission wavelength covering the targeted spectral band. The main advantage of this design is its compactness and the potential for seamless integration with existing imaging systems. This approach, however, struggles with reduced sensitivity due to the low transmission efficiency of the filters (25–65% [32], 80% [34–39], and 70–90% [33, 41]). Moreover, the ultimate resolution is determined by the bandwidth of the filters which is relatively broad (>1 nm). While such filters might be able to resolve individual Raman features to detect the presence or absence of a certain target, they cannot be scaled to identify between large groups of targets especially when the Raman signatures of these targets are overlapping and not clearly distinct. A more recent implementation of integrated narrow-band filters on photodetectors has been reported by McClung et al. [42] and Williams [43] using metasurface-tuned and phase change materials filters, respectively. This implementation significantly improved the transmission efficiency (between 77 and 98%), but the resolution remained insufficient (5–8 nm [42]) to accurately resolve individual Raman features. Cadusch et al. [44] presented another novel approach for spectrometers based on only photodetectors which breaks the miniaturizing limits, but with low spectral resolution for Raman identification applications.

In this paper, we theoretically developed a novel spectrometerless approach for direct Raman identification using metasurface-powered guided mode resonances (GMR) filters. Unlike filter-based spectrometry approaches, here the identification is entirely performed at the hardware level with a very compact design and with no post-processing of the spectral data. Typical Raman-based identification utilizes optical spectrometers to collect the full spectral features of the targets and then process these collected data to classify the targets. Alternatively, we can pre-determine the unique features and the particular regions-of-interest in the targeted Raman signatures and only measure the spectral strength at these spectral lines. This can be achieved by using tailored optical filters integrated on an imaging sensor as illustrated in Figure 1A. Here, each filter is tailored such that its transmission characteristics are matched with the specific Raman features

Figure 1: (A) Schematic of our spectrometerless Raman identification approach utilizing GMR filters. Each filter is matched with pre-selected features in the Raman spectrum of a certain target (e.g., a pathogenic bacterium). Targets can be identified by monitoring the filters with maximum transmission. (B) Schematic and (C) the transmission characteristics of a GMR filter consisting of a sub-wavelength grating sandwiched between two identical distributed Bragg reflectors (DBRs). The filter design parameters are the thin film thicknesses ($t_n = 973 \text{ nm}/4n$ and $t_g = 973 \text{ nm}/4n_{\text{eff}}$), grating periodicity ($p = 380 \text{ nm}$), two top and bottom DBR pairs, and grating: SU-8/SiO₂. (D) and (E) The labeled transmission peaks I and II and the corresponding electric field intensity distribution.

of a certain target (e.g., a pathogen or a chemical compound). Hence, the maximum transmitted optical intensity through a given filter is only achieved upon the imaging of

its matched target. Consequently, different areas on the imaging sensor light up depending on the target. Successful implementation of this approach requires optical filters with very efficient transmission characteristics and narrow line-width. Moreover, the number of the filters' transmission peaks, their line-width, and their relative spectral positions need to be customizable so that they can be matched to the Raman features of different targets. Here, we propose metasurface-powered GMR filters that meet all these optical and design-flexibility requirements to deliver accurate and instant spectrometerless Raman-identification. Notably, GMR filters possess two key features: high transmission efficiency and narrow bandwidth transmission peaks [45, 46]. To tailor their transmission characteristics for certain Raman features, we utilize the versatility of subwavelength metasurface gratings [45–48]. Our study explores the filters design parameters space and establishes a systematic design flow for our proposed spectrometerless Raman identification approach. We also theoretically validate this approach in two identification problems; saccharides identification and pathogenic bacteria classification.

2 Architecture and design methodology

Figure 1B shows a schematic of our filter design. The filter consists of a sub-wavelength metasurface grating made of two different dielectric materials (SiO_2 with $n_{\text{SiO}_2} = 1.452$ and SU-8 with $n_{\text{SU-8}} = 1.562$) sandwiched between two identical DBRs. The DBRs consist of alternating layers of two materials with high (e.g., GaP, $n_{\text{GaP}} = 3.163$) and low (e.g., SiO_2 , $n_{\text{SiO}_2} = 1.452$) refractive indices and with negligible loss in the band of interest (e.g., 800–900 nm). For proper filtering, the DBRs have to provide maximum reflectance within the spectral band of interest [33]. Thus, the thickness of each layer (t_n) is taken to be $(\lambda/4n)$ where λ is the central wavelength of the targeted spectral range [46], and n is the material's refractive index. Without the metasurface grating, the structure acts as a Fabry–Perot (FP) filter with central wavelength determined by the resonance wavelength of the cavity formed between the two reflectors [33]. Such FP filters provide relatively narrow transmission bandwidth with high transmission efficiency and reasonable tunability. However, effective Raman identification still requires sharper transmission peaks with better customizability for the number of the transmission peaks and their relative positions within the targeted spectral range. Remarkably, these functionalities can be

obtained by introducing the metasurface grating within the filter cavity. In this case, the combined structure would act as a multilayer dielectric waveguide that supports multiple guided modes which can be efficiently excited by the grating giving rise to sharp transmission peaks with minimal losses.

For a general multilayer waveguide, all the supported guided modes can be obtained by calculating the dispersion relation to find the propagation constants that satisfies the boundary conditions at the various interfaces [49]. These guided modes can be selectively excited when the propagation constant of an incident wave is matched to the propagation constant of one of the guided modes. In our filter design, this matching is achieved through the wave diffraction by the subwavelength grating [47, 50, 51]. Notably, the matching process can be tuned by tweaking the subwavelength grating design and materials. Remarkably, these excited guided modes are also out-coupled by the subwavelength grating to interfere destructively (constructively) with the reflected (transmitted) waves giving rise to resonant transmission peaks with very narrow linewidth. A thorough model of this resonant behavior has been developed by Wang et al. [47] and is briefly described in the Supplementary Section S1.

The transmission spectra of the GMR filter shown in Figure 1B is depicted in Figure 1C. The metasurface grating of this filter has a thickness $t_g = 161$ nm, width $w = 190$ nm, and period $p = 380$ nm. The two DBR pairs encapsulating the grating each consist of two pairs of GaP/ SiO_2 with thicknesses $t_n(\text{GaP}) = 77$ nm, $t_n(\text{SiO}_2) = 168$ nm. These dimensions are chosen such that the filter operates optimally in the 800–900 nm spectral band as will be explained later. This is the typical wavelength range of interest for Raman spectroscopy assuming an excitation wavelength of 785 nm – a typical Raman excitation wavelength especially for biological applications [52]. In this work, we used rigorous coupled wave analysis [53] to design and characterize these metasurface-powered GMR filters. For an incident linearly-polarized plane wave with the incident electric field along the y-axis, this filter element is characterized by four sharp transmission peaks in the region of interest as shown in Figure 1C. Besides their narrow linewidth, the transmission efficiency of these peaks ranges between 98.8 and 99.6%. Note that the cavity length between the two DBR mirrors is determined by the grating thickness and is picked such that the Fabry–Perot resonance wavelength of this structure is out of the band of interest as shown in Figure S1. This is achieved for this spectral band of interest when the grating thickness (t_g) equals $\lambda/4n_{\text{eff}}$, where λ is the free-space wavelength and n_{eff} is the effective refractive

index of the grating layer. The two transmission peaks at 855.9 and 878.1 nm (labeled as I and II) and the corresponding electric field intensity distribution within the filter are shown in Figure 1D and E. The figures demonstrate the sharp nature of these resonances where the full-width at half-max (FWHM) of peaks I and II are 254 MHz ($Q = 1.4 \times 10^6$) and 14.1 GHz ($Q = 24 \times 10^3$), respectively. Where, Q is the quality factor. Notably, the electric field intensity distribution within the filter at these two resonances matches that of the first two modes supported by the multilayer waveguide formed by the two DBR pairs (Figure S2). Since our filter design is based on 1D sub-wavelength grating, the filter response depends on the polarization of the incident wave (Figure S3).

3 Raman tailored filter design parameters

One of the great merits of this GMR filter is its design flexibility and the ability to tailor its transmission characteristics to target particular spectral lines as mandated by Raman-identification applications. This filter has five main design parameters: the DBR thin film thicknesses (t_n),

the periodicity of the sub-wavelength metasurface grating (p), the number of the DBR thin film pairs (N), the grating material choice, and the grating filling factor (f). The effect of the DBR thin film thickness (t_n) is illustrated in Figure 2A. The figure indicates that as t_n increases from 943 nm/ $4n$ to 1003 nm/ $4n$ (substituting n with either n_{GaP} or n_{SiO_2}), the separation between the transmission peaks is reduced by about 5 nm with a 20 nm overall red-shift in their wavelength. By changing t_n , the guided modes supported by the multilayer waveguide are modified [54] and the filter transmission peaks are tuned accordingly. Note that, in principle, the two DBR layers are designed to maximize the reflection away from the transmission peaks to ensure strong rejection for the undesired wavelengths. This is achieved when the thickness of the DBR thin films is $\lambda_{\text{target}}/4n$ (n_{GaP} or n_{SiO_2}) as mentioned earlier. However, Figure 2A indicates that t_n can be tweaked around this optimal value without compromising the off-resonance filter rejection. This facilitates fine-tuning of inter-peak separation with minimal effect on the filter performance. When t_n starts to have a significantly higher/lower value away from the optimal, the off-resonance rejection starts to deteriorate. For example, when t_n changes from 943 nm/ $4n$ to 1003 nm/ $4n$, the average off-resonance transmission increases from 2 to 9%.

Figure 2: The design parameters for the metasurface powered GMR filter.

(A) The change in the filter transmission characteristics with the thicknesses ($t_n = 1003 \text{ nm}/4n$ and $t_g = 1003 \text{ nm}/4n_{\text{eff}}$), ($t_n = 973 \text{ nm}/4n$ and $t_g = 973 \text{ nm}/4n_{\text{eff}}$) and ($t_n = 943 \text{ nm}/4n$ and $t_g = 943 \text{ nm}/4n_{\text{eff}}$) for period $p = 380 \text{ nm}$, two DBR pairs, filling factor (f) = 0.5 and SU-8/SiO₂ grating. (B) Tuning the filters' transmission wavelengths with the grating periodicity (p) with constant design value of $t_n = 943 \text{ nm}/4n$, $t_g = 943 \text{ nm}/4n_{\text{eff}}$, two DBR pairs, $f = 0.5$ and SU-8/SiO₂ grating. (C) Controlling the number of the filter transmission peaks with the number of DBR pairs for constant values of $t_n = 973 \text{ nm}/4n$, $t_g = 973 \text{ nm}/4n_{\text{eff}}$, $p = 380 \text{ nm}$, $f = 0.5$ and SU-8/SiO₂ grating. (D) The effect of changing the grating layer for constant values of $t_n = 973 \text{ nm}/4n$, $t_g = 973 \text{ nm}/4n_{\text{eff}}$, $p = 380 \text{ nm}$, $f = 0.5$ and two DBR pairs. (E) Modulating the filter transmission quality factor (Q) by the changing the filling factor (f) for constant values of $t_n = 850 \text{ nm}/4n$, $t_g = 850 \text{ nm}/4n_{\text{eff}}$, $p = 400 \text{ nm}$, four DBR pairs and SU-8/SiO₂ grating.

The filter transmission peaks wavelengths can be further tuned by leveraging the metasurface grating periodicity (p). Changing the periodicity modifies the additional momentum imposed by the metasurface grating on the incident wave as explained earlier. This in turn controls the wavelengths that can be efficiently coupled into the multilayer waveguide and modifies the transmission peaks wavelengths as Figure 2B demonstrates. The figure shows that as the grating period increases from 365 to 395 nm, the transmission peaks red-shift by 50 nm to be located within the spectral range of 820–904 nm instead of 781–845 nm with a slight increase in the inter-peak separation from 21 to 27 nm. This behavior is persistent regardless of the number of DBR thin film pairs as demonstrated for an 8-layer DBR filter shown in Figure S4 where the filter supports eight transmission peaks. The number of DBR layer-pairs (N) is another crucial parameter that primarily controls the number of transmission peaks as highlighted in Figure 2C. As one would expect from waveguide theory, increasing the number of layers of the multi-layer waveguide increases the number of modes supported by the waveguide [49] (Figure S5). This in turn determines the number of the filter transmission peaks. Moreover, the number of the DBR thin film pairs controls the resonances quality-factor which dictates the bandwidth of the transmission peaks [47]. We also note that changing the number of DBR thin film pairs from four to eight pairs modifies the inter-peak separation from around 22–11 nm. This is due to the alteration of the supported guided modes as indicated by the multilayer waveguides dispersion relations (Figure S5).

The choice of the grating material is another important parameter that governs the filter performance and characteristics. Particularly, the refractive index contrast of the grating (grating modulation) affects the quality factor of the filter resonances. Namely, as the contrast decreases, the quality factor increases [46] as depicted in Figure 2D. The figure also shows that higher refractive index contrasts leads to more nonuniform transmission peaks distributions and can even force some of the transmission peaks to fall out of the spectral band of interest. This is due to the modulation of the multilayer waveguide modes and the corresponding waveguide dispersion relation (Figure S6) as the effective refractive index of the grating layer increases (Section S2).

The final design parameter we consider is the filling factor (f). It is defined as the ratio between the width of the high refractive index material of the grating and the grating period. As depicted in Figure 2E, when the filling factor (f) moves away from 0.5 toward either 0 or 1, the

quality factor increases from about 5.1×10^7 to 5.4×10^8 which leads to transmission peaks with narrower FWHM [46]. We summarize all these design parameters and their effects in Table S1.

4 Results and discussion

The diverse design parameters of our proposed filter allow us to tailor the filter transmission characteristics to match particular Raman features of targeted specimens. Consequently, direct identification could be achieved without sophisticated instrumentation at considerably lower cost. To highlight this capability, we consider two different Raman identification scenarios. In particular, we evaluate the possibility of identifying four different saccharides using customized filters. We also highlight the potential of using this approach to identify two different strains of antibiotic-susceptible and resistant pathogen.

4.1 Saccharides identification

Saccharides are responsible for countless biological functions in living organisms from metabolism and energy storage to immune response [55]. They are also widely used in industry including food and pharmaceutical industry as flavors, preservatives, stabilizers, and even as masking agents for medications [56, 57].

As a case study, we picked four different saccharides (fructose, ribose, sucrose and maltose) to analyze and evaluate their identification accuracy using our approach. The distinct Raman signature of each of these molecules is shown in Figure 3A [58, 59]. Our filter design methodology is summarized in Figure S8. The first step to design our Raman-matched filters is to determine the key distinguishing Raman features of each molecule. We do so by calculating the differential Raman signature of each molecule by subtracting its normalized Raman signature (e.g., fructose) from each one in the targeted group (Figure S9). For fructose, the differential Raman characteristics indicate eight unique features. The quick examination of these eight features indicates that only three features are sufficient to accurately identify fructose against the three other targets (highlighted in Figure S9). Hence, the accurate identification of fructose can be obtained by designing its Raman-matched filter to only allow these spectral features to reach an imaging sensor. This analysis of the differential Raman signal is repeated for each of the three other saccharides to determine the distinguishing feature of each target

Figure 3: (A) The normalized Raman spectrum of the four saccharides under study. (B) The transmission characteristics of each saccharide filter. (C) The transmission spectra from the four filters for the peaks labeled in panel a (I, II, III and IV) when each filter is exposed to the four saccharides. The total optical intensity transmitted from each filter is significantly maximized for matched filter/target peaks. (D) The confusion matrix for the overall identification accuracy for each saccharide.

(Figure S9). We note that for both fructose and ribose, three features are sufficient for accurate identification, while only two features are needed for the sucrose and maltose.

Once specified, we can now customize our filter design and create a matched filter for each target.

The main design inputs are the number of Raman features, their wavelengths, and their linewidth. The number of Raman features specifies the number of the filter transmission peaks and consequently determines by the number of the filter DBR pairs (N). Even though Raman filters with two or three DBR pairs would be sufficient to identify the four targets, we choose to design all the filters with four DBR pairs to ensure strong rejection of the out-of-resonance wavelengths. This results in filters with four transmission peaks. We then tune the filters design to push the extra transmission peaks out of the band of interest and have only three transmission peaks (in the case of fructose and ribose) or two transmission peaks (in the case of sucrose and maltose) aligned to their respective Raman features. This tuning can be primarily achieved through proper design of the sub-wavelength grating layer. To showcase the flexibility of the filter design, we used GaP/SU-8 grating for the sucrose and maltose (two peaks), while we used SU-8/SiO₂ grating for the fructose and ribose (three peaks) with a filling factor (f) of 0.5. The initial grating period (p) of the four saccharides filters (fructose, ribose, sucrose and maltose) is picked to be 373 nm, 379 nm, 406 nm, and 430 nm, respectively, to obtain initial matching between the filters' transmission peaks and the Raman peaks of the targets. Lastly, the initial t_n value is taken to be $850 \text{ nm}/4n$, where n is the refractive index of the thin film materials of DBRs (SiO₂ and GaP). As we explained earlier, this choice ensures strong rejection of the out-of-resonance wavelengths in the spectral band of interest assuming a Raman excitation wavelength of 785 nm. Similarly, t_g equals to $850/4n_{\text{eff}}$, where n_{eff} is the effective refractive index of the grating (either SU-8/SiO₂ or GaP/SU-8). This is an adequate choice to force the Fabry–Perot resonance to be outside the spectral band of interest.

After specifying these initial design parameters, the final step is to optimize the design to perfectly align the filter resonances with the key Raman features of the targets and maximize the classification accuracy. As previously discussed, the impact of the various design parameters on the filter characteristic is somewhat coupled. Thus, simultaneous optimization, particularly for t_n and p , is required to tune both the transmission peaks wavelength and the inter-peak separations. We performed this final optimization process by running comprehensive parameter-sweep around the initial values of the design parameters. The final transmission characteristics of the four identification filters are shown in Figure 3B with their corresponding design parameters summarized in Table S2. Note that other

combinations of design parameters and/or materials are also possible.

To benchmark the accuracy of our identification approach, we calculate the total transmitted optical intensity through each filter when exposed to the Raman spectra of each saccharide. To simplify this analysis, we use the normalized spectra shown in Figure 3A and assume that the total optical power scattered into the Raman spectra is the same for each molecule. Figure 3C highlights the transmitted optical spectrum through the indicated filter peaks for each saccharide. The figure demonstrates that the total transmitted intensity is maximized for matched filter/target peaks. The overall identification accuracy for each saccharide is illustrated by the confusion matrix in Figure 3D. Here, the total transmitted intensity from a certain filter is normalized by the total intensity from the same filter when exposed to its matched target. The confusion matrix indicates that for the four targets we considered, the total transmitted intensity for matched filter/target pairs is at least twice as high compared to that from any unmatched filter/target pair. Hence, direct saccharide identification can be directly achieved by measuring filtered signals.

One of the major advantages of these metasurface-enabled GMR filters is the ability to tune the width of the filter transmission peaks to be sufficiently sharp for Raman identification. The impact of increasing the transmission peak linewidth on the identification accuracy is illustrated in Figure 4. The figure shows the transmission characteristics of the ribose-identification filter with two different gratings (SU-8/SiO₂ vs. GaP/SU-8) while keeping all the other design parameters as summarized in Table S2. The FWHM of the two filters is 0.013 and 0.7 nm, respectively. The significance of this change on the identification accuracy is highlighted in Figure 4C. Even with the 0.7 nm transmission peak linewidth, we see that the accuracy significantly drops due to the increase in the background transmission from other targets.

4.2 Methicillin resistant and susceptible *S. Aureus* identification

Pathogen detection and identification is another area where Raman spectroscopy promises to enable rapid and cost-effective point-of-care diagnostics. Our proposed spectrometerless Raman identification would bring such Raman-based techniques to the clinics in a practical and more economic way. Here, we lay the foundation for our spectrometerless identification of two crucial *S. aureus* strains; methicillin-resistant *S. aureus* (MRSA) and methicillin-susceptible *S. aureus* (MSSA). MRSA is identified by the Center of Disease Control (CDC) to be one of the

B

Normalized Spectral Power	Ribose Filter	
	FWHM=0.7nm	FWHM=0.013nm
Fructose	0.19	0.11
Ribose	1	1
Sucrose	0.74	0.5
Maltose	0.68	0.39

Figure 4: (A) The transmission characteristics of the ribose identification filter with two different gratings (SU-8/SiO₂ and GaP/SU-8). The insets show an enlarged figure for the shorter-wavelength peak indicating the difference in the two peaks' linewidths. (B) The confusion matrix for the identification accuracy of ribose using the two filters.

serious threats facing our generation [60]. It is responsible for many hospital acquired infections [61] and is becoming increasingly difficult to treat due to its growing antibiotic resistance. Thus, providing a simple and rapid identification tool to distinguish resistant and susceptible strains is of extreme importance.

Figure 5A depicts the Raman signature of MSSA2 and MRSA2 strains as has been reported by Ho et al. [16]. Following the same design approach we described earlier, we first obtain the Raman differential signal of our two targets and determine the required filter characteristics. Analyzing the differential signal indicates that designing filters with two transmission peaks would be sufficient for accurate classification. The filter transmission characteristics of the MSSA2/MRSA2 identification are depicted in Figure 5B with its design parameters summarized in Table S3. The transmitted intensity spectra around peak (I) of the MSSA2 and peak (II) of the MRSA2 are shown in

Figure 5: Raman identification analysis for pathogenic bacteria case study.

(A) The normalized Raman spectrum of methicillin-resistant *S. aureus* (MRSA2) and methicillin-susceptible *S. aureus* (MSSA2) targeted bacteria [16]. (B) The transmission characteristics of the Raman-matched filter for the two strains shown in (A). (C) The transmitted intensity spectra through the indicated filter peaks for each strain. (D) The confusion matrix for the overall identification accuracy for the two pathogenic strains.

Figure 5C. Similar to our previous results, the transmission efficiency is maximized for matched filter/target pairs. The confusion matrix shown in Figure 5D indicates that direct

classification of resistant and susceptible *S. aureus* can be accurately achieved through direct Raman imaging with our spectrometerless approach. This lays the foundation toward cost-effective, point-of-care Raman based pathogen classification that has the potential to save millions of lives and provide accessibility to quality healthcare even under resource-limited conditions.

5 Conclusion and outlook

In summary, we have introduced a novel spectrometerless Raman identification using GMR filters. By leveraging subwavelength metasurface gratings, we have shown that the filter transmission characteristics can be tailored for specific Raman signatures without compromising the transmission efficiency. Our simulations indicate that our filtering approach can achieve a resolution as high as 0.06 cm^{-1} to match even the finest details in a Raman signature. We have also demonstrated the promise of this platform for accurate Raman-based identification using two different case studies of saccharides and pathogenic bacteria. Our filter design uses CMOS-compatible materials and can be fabricated with current subwavelength optical lithography techniques used in the semiconductor industry. Thus, it can be readily integrated with commercial imaging sensors making it cost-effective and scalable. The remarkable flexibility and simplicity of our identification methodology makes it adoptable to countless other targets. It can be integrated with advanced data analysis techniques that employ machine-learning and artificial intelligence to directly identify targets even when the differences between the distinguishing Raman features are quite subtle. Moreover, this filter design can utilize more sophisticated metasurface designs to tailor the filter response to other optical responses such as Raman optical activity of chiral molecules. Beyond identification, our platform can be also utilized in quantitative analysis of targets. For example, it can be used to estimate analyte concentrations in mixtures through pre-determined calibration curves [62]. It can be combined with other data analysis approaches such as multivariate analysis methods [63] and deep learning methods [64] to provide quantitative information about the targets. In this case, our tailored Raman filters have the potential to simplify the implementation and even improve the performance of these methods by reducing the size of spectral data collected and only acquiring the most relevant Raman features. Our Raman identification architecture promises to be the foundation for a new generation of wearable health monitors and point-of-care platforms that meet the demands of

personalized medicine. It can be also used for inline monitoring in pharmaceutical production lines, food industry, and even waste treatment facilities. With this spectrometerless approach, we pave the way to overcome some of the major milestones that hindered wide adoption of Raman spectroscopy in various fields.

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