

Super-resolution Raman imaging towards improved visualisation of nanoplastics

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Supporting Information

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1. Figure S1 / Table S1: More information for Figures 2-3

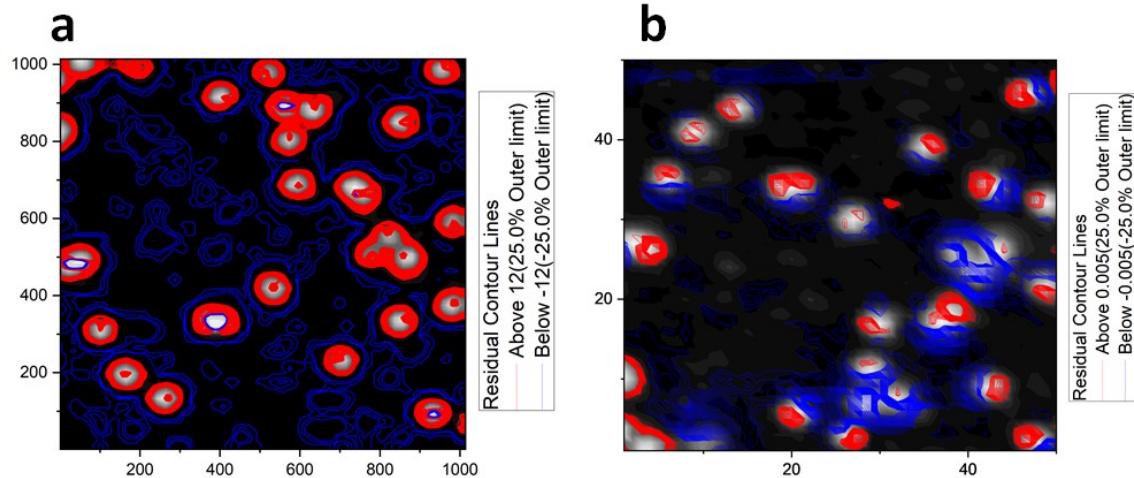


Figure S1. Fitting residues for Figures 2-3. (a) is for Figure 2 (without PCA) while (b) is for Figure 3 (with PCA).

Figure S1 shows the fitting residues. In (a), while the strong signals are paid more attention, the weak signal has a very limited contribution, which needs more research. Particularly, once these weak signal can be confirmed as the nanoplastics, the fitting should covered them as well to re-construct the image, as shown in Figure 3 and in (b). Note the fitting in (a) starts up from the Raman intensity image with a pixel of 1024×1024 , while (b) starts up from the loading coefficient of an array of 50×50 .

Table S1. Parameters Summary for the fitting peaks (all data for the $x \times y$ axis of 1014×1014 , after removing boundary from 1024×1024 of the image with size of $10 \mu\text{m} \times 10 \mu\text{m}$). The highlight (in yellow) marks the peaks for Figures 2(i, j).

	z0		A		xc		w1		yc		w2		FWHMx		FWHMy	
	Value	Standard Error	Value	Standard Error	Value	Standard Error	Value	Standard Error	Value	Standard Error	Value	Standard Error	Value	Standard Error	Value	Standard Error
Peak1(Sheet1)	18.38568	-235.61432	--	50	--	11	--	482	--	7.68987	--	25.90302	--	018.10825	0	
Peak2(Sheet1)	18.38568	-235.61432	--	61	--	-10.09146	--	482	--	7.10049	--	23.76356	--	016.72038	0	
Peak3(Sheet1)	18.38568	-235.61432	--	39	--	11	--	482	--	7.35467	--	25.90302	--	017.31892	0	
Peak4(Sheet1)	18.38568	-235.61432	--	28	--	-12.76591	--	482	--	7.35095	--	30.06143	--	017.31016	0	
Peak5(Sheet1)	18.38568	-235.61432	--	738	--	5.68465	--	666	--	4.794	--	13.38633	--	011.28901	0	

Peak6(Sheet1)	18.38568	--235.61432	--410	--5.68465	--338	--7.68987	--13.38633	018.10825	0
Peak7(Sheet1)	18.38568	--235.61432	--403	--9	--338	--9.5642	--21.19338	022.52198	0
Peak8(Sheet1)	18.38568	--235.61432	--392	--11	--338	--7.35467	--25.90302	017.31892	0
Peak9(Sheet1)	18.38568	--235.61432	--756	--17.47346	--666	--7.35095	--41.14685	017.31016	0
Peak10(Sheet1)	18.38568	--235.61432	--390	--12.76591	--318	--4.21869	--30.06143	0 9.93425	0
Peak11(Sheet1)	18.38568	--235.61432	--389	--17.27454	--325	--12.76591	--40.67842	030.06143	0
Peak12(Sheet1)	18.38568	--235.61432	--370	--7.35467	--338	--8.18595	--17.31892	019.27645	0
Peak13(Sheet1)	18.38568	--235.61432	--381	--11	--338	--10.06029	--25.90302	023.69018	0
Peak14(Sheet1)	18.38568	--235.61432	--861	--8.97483	--502	--6.36249	--21.1341	014.98252	0
Peak15(Sheet1)	18.38568	--234.61432	--164	--12.66748	--195	--6.8439	--29.82962	016.11616	0
Peak16(Sheet1)	18.38568	--234.61432	--267	--9.20559	--134	--8.00881	--21.67751	0 18.8593	0
Peak17(Sheet1)	18.38568	--234.61432	--860	--10.57892	--338	--6.8439	--24.91145	016.11616	0
Peak18(Sheet1)	18.38568	--234.61432	--942	--8.4191	--93	--6.50569	--19.82546	015.31974	0
Peak19(Sheet1)	18.38568	--234.61432	--554	--6.34886	--891	--7.04577	--14.95042	016.59152	0
Peak20(Sheet1)	18.38568	--234.61432	--22	--10.34517	--482	--9.20559	--24.36102	021.67751	0
Peak21(Sheet1)	18.38568	--234.61432	--934	--9.5	--93	--6.50569	--22.37079	015.31974	0
Peak22(Sheet1)	18.38568	--234.61432	--923	--7.97825	--93	--6.50569	--18.78735	015.31974	0
Peak23(Sheet1)	18.38568	--234.61432	--561	--12.73874	--891	--6.25576	--29.99743	0 14.7312	0
Peak24(Sheet1)	18.38568	--233.61432	--574	--6.3352	--809	--7.32319	--14.91825	017.24478	0
Peak25(Sheet1)	18.38568	--233.61432	--572	--14.50212	--891	--7.29021	--34.14989	017.16714	0
Peak26(Sheet1)	18.38568	--233.61432	--594	--9.26266	--687	--6.4917	--21.8119	015.28678	0
Peak27(Sheet1)	18.38568	--233.61432	--635	--7.9409	--890	--11.37935	--18.69939	026.79631	0
Peak28(Sheet1)	18.38568	--233.61432	--983	--9.3218	--379	--6.82919	--21.95117	016.08152	0
Peak29(Sheet1)	18.38568	--233.61432	--533	--9.99679	--420	--8.823	--23.54064	020.77657	0
Peak30(Sheet1)	18.38568	--231.61432	--859	--12.76346	--850	--7.70846	--30.05565	018.15204	0
Peak31(Sheet1)	18.38568	--228.61432	--410	--9.08654	--912	--5.49379	--21.39717	0 12.9369	0
Peak32(Sheet1)	18.38568	--224.61432	--103	--6.21088	--317	--10.60366	--14.62551	024.96971	0
Peak33(Sheet1)	18.38568	--210.61432	--697	--14.51675	--236	--5.92406	--34.18433	013.95009	0
Peak34(Sheet1)	18.38568	--204.61432	--963	--8.59387	--993	--8.36909	--20.23702	019.70769	0
Peak35(Sheet1)	18.38568	--193.61432	--820	--6.21228	--563	--9.83776	--14.6288	023.16616	0
Peak36(Sheet1)	18.38568	--173.61432	--984	--6.59385	--584	--9.95422	--15.52733	023.44039	0
Peak37(Sheet1)	18.38568	--164.61432	--513	--7.98692	--973	--9.69053	--18.80777	022.81944	0
Peak38(Sheet1)	18.38568	--151.61432	--779	--6.15823	--502	--9.29644	--14.50152	021.89144	0
Peak39(Sheet1)	18.38568	--84.61432	--185	--11.45345	--994	--5.38304	--26.97082	012.67609	0
Peak40(Sheet1)	18.38568	--54.61432	--1004	--3.50268	--72	--5.21737	--8.24818	012.28597	0
Peak41(Sheet1)	18.38568	--12.61432	--686	--2.89694	--912	--2.89694	--6.82176	0 6.82176	0
Peak42(Sheet1)	18.38568	--6.61432	--901	--3.08455	--563	--3.08455	--7.26357	0 7.26357	0
Peak43(Sheet1)	18.38568	--4.61432	--226	--1.68456	--543	--2.46706	--3.96683	0 5.80949	0
Peak44(Sheet1)	18.38568	--4.61432	--243	--1.68456	--543	--1.68456	--3.96683	0 3.96683	0
Peak45(Sheet1)	18.38568	--4.61432	--233	--1.68456	--544	--2.49907	--3.96683	0 5.88486	0
Peak46(Sheet1)	18.38568	--3.61432	--185	--1.46287	--51	--1.98225	--3.44481	0 4.66784	0

2. Figure S2 / Table S2: More information for Figure 3

2.1. PCA analysis parameters for Figure 3

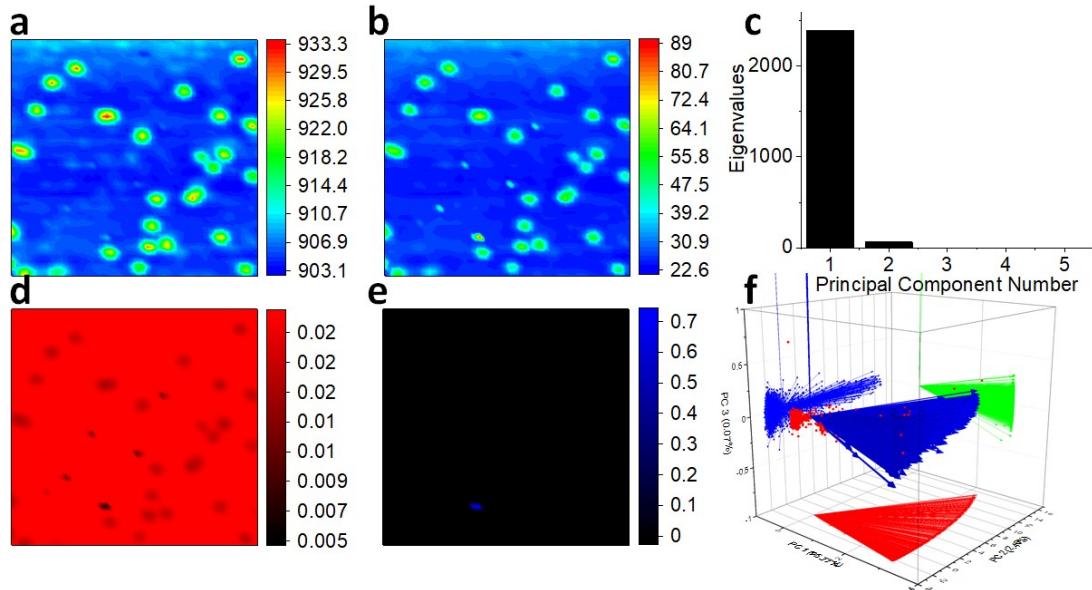


Figure S2. PCA analysis on the raw data in Figure 2, including the mapped mean (a), standard variation (b), scree plot (c), mapped coefficients of PC1 (d) and PC3 (e), loading plot (f).

Figure S2 shows the PCA analysis parameters for Figure 3. The mapped mean can tell us where the main signal (or main variance) are collected. The mapped variation reminds us where the PCA calculation is not so confident and we should be cautious to draw the conclusion. Scree plot indicates the main variance of PCA analysis is taken in PC1 and PC2.

The mapped coefficients of PC1 and PC3 can support the assignment of PC1 to background, and PC3 to noise, such as cosmic ray from the detector. The loading plot implied that most of the PCs are independent from each other.

Peak42(PC2)	0.00483	-	-	-	-	-	-	0	-	-	-	0	-	0	0	0	0	0	-
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3. Figure S3 / Table S3: More information for Figures 4-5

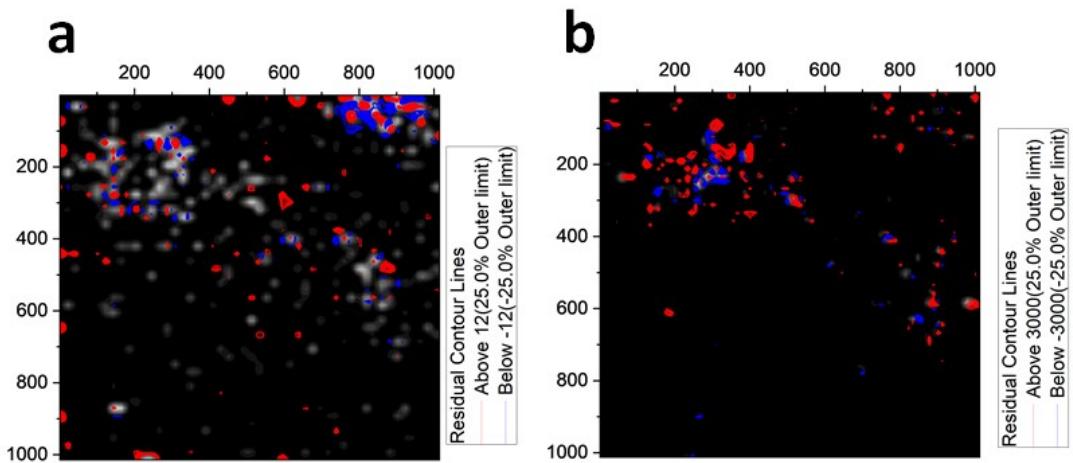


Figure S3. Fitting residue for Figures 4-5. (a) is for Figure 4 while (b) for Figure 5.

Due to the weak signal and the computation complexity, there are lots of spots that are not picked up for fitting in (a). This limit also corresponds with the image resolution issue discussed in the main manuscript. That is, we must balance among the high resolution imaging (to capture nanoplastics down to < 100 nm), the scanning duration, the signal intensity and the computation capacity etc.

This fitting residue in (b) looks better than (a), because the logic-based algorithm has filtered lots of noise towards fitting.

Table S3. Parameters Summary for the fitting peaks (all data for the x × y axis of 1014× 1014, after removing boundary from 1024× 1024 of the image with size of 2 μm × 2 μm). The highlight (in yellow) marks the peaks for Figures 3(i, j).

Peak183(She et1)	179.151	0.4422	2043.001	83.60911	872	0.30549	5.85395	0.28348	661	0.28378	38.4571	2	0.98212	13.78499	0.66755	90.5595	9	2.31272
Peak184(She et1)	179.151	0.4422	2536.585	1.83921E8	471	0.012788	8.7346E-11	0.62449	255	265.829	0.23622	84	65.683512.08954E-10	1.47057	0.55626	154.67285		
Peak185(She et1)	179.151	0.4422	1802.020	115.46255	511	0.69961	8.94505	0.30071	384	0.364023.52642	0.40756	21.06398	0.708128.30407	0.95973				
Peak186(She et1)	179.151	0.4422	4276.593	53.17595	471	0.25157	40.37579	0.42992	258	0.3349720.7772	1	0.28624	95.07773	1.01238	48.9265	8	0.67404	
Peak187(She et1)	179.151	0.4422	5423.862	239.8821	93	0.14641	2.30306	0.13928	72	0.564627.38722	1	0.49614	5.4233	0.32798	17.3955	8	1.16831	
Peak188(She et1)	179.151	0.4422	5017.183	389.60776	887	0.17369	2.6879	0.17669	341	0.591817.52212	0.42269	6.32951	0.41607	17.7132	4	0.99536		
Peak189(She et1)	179.151	0.4422	4198.086	358.20105	668	0.23276	3.73164	0.24255	499	0.623678.56877	0.43132	8.78733	0.57115	20.1779	2	1.01569		
Peak190(She et1)	179.151	0.4422	2839.271	130.5393	797	0.3009	10.12203	0.44059	420	0.4305916.2722	1	0.47007	23.83557	1.03752	38.3181	3	1.10694	
Peak191(She et1)	179.151	0.4422	2443.427	412.06366	193	0.77808	4.5406	0.56967	412	0.774824.13371	0.52752	10.69229	1.34147	9.73414	1	1.24222		
Peak192(She et1)	179.151	0.4422	5056.578	318.17257	872	0.15895	2.38271	0.15246	339	0.383927.41922	0.3727	5.61086	0.35901	17.4709	2	0.87764		
Peak193(She et1)	179.151	0.4422	4156.965	383.17033	632	0.30269	7.917	0.4813	508	0.234443.30432	0.23884	18.64311	1.13337	7.78108	0.56244			
Peak194(She et1)	179.151	0.4422	2100.232	247.76842	855	0.76985	6.77258	0.51092	297	0.670238.84057	0.6496	15.9482	1.20311	20.8179	6	1.52969		
Peak195(She et1)	179.151	0.4422	3139.439	311.01873	706	0.61788	4.80323	0.51285	23	0.48614.569	0.4804	11.31074	1.20766	10.7591	7	1.13126		
Peak196(She et1)	179.151	0.4422	3527.153	202.97621	163	0.28273	8.84976	0.38646	133	0.384166.0078	0.34291	20.8396	0.91003	14.1472	8	0.80749		
Peak197(She et1)	179.151	0.4422	3347.036	498.50888	564	0.57079	3.87611	0.42072	735	0.547253.79834	0.41619	9.12753	0.99071	8.94442	0.98005			
Peak198(She et1)	179.151	0.4422	1645.509	246.46597	655	1.39441	9.24279	0.81733	94	0.839576.88796	0.6333	21.76511	1.92465	16.2199	2	1.49131		
Peak199(She et1)	179.151	0.4422	4746.567	302.36071	320	0.18074	2.28987	0.16122	379	0.621027.20735	0.44689	5.39222	0.37964	16.9720	1	1.05235		
Peak200(She et1)	179.151	0.4422	3460.430	439.81296	264	0.715	8.0696	0.59471	935	0.320512.64961	0.25752	19.00245	1.40044	6.23934	0.60642			

5. Gaussian surface fitting code (Generated by ChatGPT)

```
import numpy as np
from scipy.optimize import curve_fit

# Define the Gaussian function
def gaussian_surface(xy, A, x0, y0, sigma_x, sigma_y):
    x, y = xy
    return A * np.exp(-((x - x0) ** 2) / (2 * sigma_x ** 2) - ((y - y0) ** 2) / (2 * sigma_y ** 2))

# Generate example data (replace with your actual data)
x_data = ...
y_data = ...
z_data = ...

# Perform the curve fitting
initial_guess = [1.0, 0.0, 0.0, 1.0, 1.0] # Initial parameter guess
popt, pcov = curve_fit(gaussian_surface, (x_data, y_data), z_data, p0=initial_guess)

# Extract the fitted parameters
```

```

A_fit, x0_fit, y0_fit, sigma_x_fit, sigma_y_fit = popt

# Evaluate the fitted Gaussian surface
x_eval = ... # Replace with the x-values at which you want to evaluate the surface
y_eval = ... # Replace with the y-values at which you want to evaluate the surface
z_fit = gaussian_surface((x_eval, y_eval), A_fit, x0_fit, y0_fit, sigma_x_fit, sigma_y_fit)

# Print the fitted parameters
print("Fitted Amplitude (A):", A_fit)
print("Fitted x0:", x0_fit)
print("Fitted y0:", y0_fit)
print("Fitted Sigma_x:", sigma_x_fit)
print("Fitted Sigma_y:", sigma_y_fit)
*****

```

Make sure to replace `x_data`, `y_data`, and `z_data` with your actual data arrays. Also, provide appropriate values or arrays for `x_eval` and `y_eval` to evaluate the fitted surface at desired points.

This code assumes that you have NumPy and SciPy libraries installed. If you don't have them, you can install them using `pip install numpy scipy`.

Please note that this is a basic example, and you may need to adjust it according to your specific requirements and data structure.

6. Real sample #3: mixture

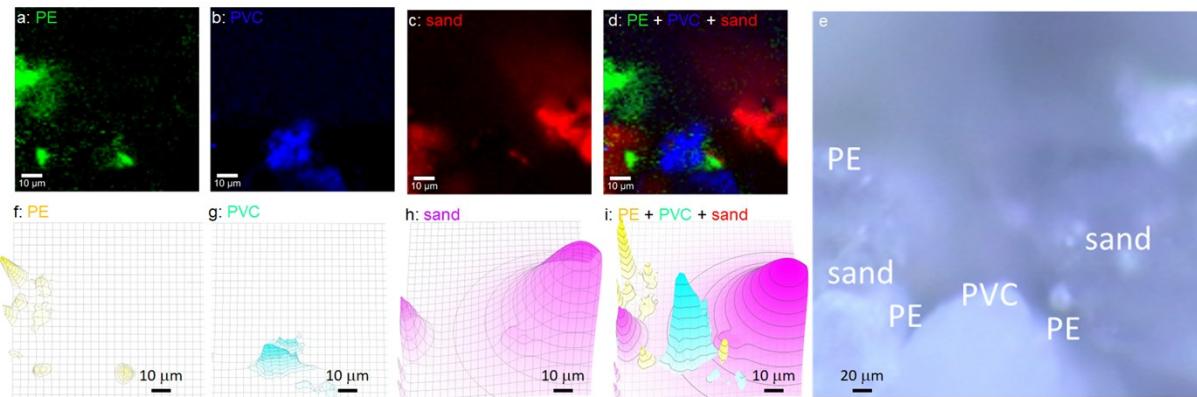


Figure S4. Raman images (a-d), re-constructed images (f-i) and photo image (e). The sample was a mixture of sand, PE and PVC. Raman images (a-d) are mapped via their characteristic peaks at ~1059

cm^{-1} for PE, $\sim 695 \text{ cm}^{-1}$ for PVC, and $\sim 520 \text{ cm}^{-1}$ for sand, and re-construct as (f-i), respectively. (d, i) merges them to show the mixture of plastics and sand. (e) shows a photo image for comparison with the items identified by Raman.

A mixture is analysed in this section, including PE, PVC and sand¹. The mapping and imaging are based on their characteristic peaks towards identification. The images (a-c) can be re-constructed as (f-h), individually. The mixture can be visualised in (d) and (i), before and after the re-construction. The imaging and assignment certainty can be significantly increased by the image re-construction. Compared to the photo image in (e), the advantage of Raman imaging is obviously demonstrated, along with the image re-construction. That is, the reported approach can effectively identify and visualise the mixture containing the different plastics and other items, which cannot be achieved in the photo image.

Reference

1. Z. Sobhani, M. Al Amin, R. Naidu, M. Megharaj and C. Fang, *Analytica Chimica Acta*, 2019, **1077**, 191-199.