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# Regressing bubble cluster dynamics as a disordered many-body system

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The coherent dynamics of bubble clusters are of fundamental and industrial importance 7 and are elusive due to the complex interactions of disordered bubble oscillations. Here 8 we introduce and demonstrate a method for decomposition of the Lagrangian time series 9 of bubble dynamics data by combining theory and principal component analysis. The 10 decomposition extracts coherent features of bubble oscillations based on their energy, in 11 a way similar to Proper Orthogonal Decomposition of Eulerian flow field data. This method 12 is applied to a data set of spherical clusters under harmonic excitation at different amplitudes, 13 with various nuclei density and polydispersity parameters. Results indicate that the underlying 14 correlated mode of oscillations is isolated in a single dominant feature in cavitating regimes, 15 independent of nuclei's parameters. A systematic data analysis procedure further suggests 16 that this feature is globally controlled by the dynamic cloud interaction parameter of Maeda 17 and Colonius (J. Fluid Mech., vol. 862, 2019, pp. 1105-1134) that quantifies the mean-18 field interactions, regardless of initial polydispersity or nonlinearity. The method provides a 19 simplified and comprehensive representation of complex bubble dynamics as well as a new 20 path to reduced-order modeling of cavitation and nucleation. 21

22 Key words: Bubble dynamics, Cavitation

## 23 MSC Codes (Optional) Please enter your MSC Codes here

## 24 **1. Introduction**

25 Cavitation bubble clusters nucleate when the liquid pressure rapidly falls below a certain

threshold. These clusters coherently oscillate and violently collapse to cause extreme energy

27 concentration that leads to various critical consequences and use in applications as diverse 28 concentration and guerres ( $a = Plasset \ S = Fluis 1055$ ; Plander S = Vata 1075; Marsh 1080;

as injectors and pumps (e.g., Plesset & Ellis 1955; Blander & Katz 1975; Mørch 1980;

- 29 Chen & Heister 1994; Hashimoto *et al.* 1997; Prosperetti 2017), hydraulic machines (Arndt 1081) and anything and hadrafills (a.g. Kabata et al. 1002). Maddla et al. 1008
- 1981), underwater propulsion and hydrofoils (e.g., Kubota *et al.* 1992; Merkle *et al.* 1998;
- 31 Kunz et al. 2000; Schnerr & Sauer 2001; Gnanaskandan & Mahesh 2016; Ganesh et al.
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32 2016; Venning et al. 2022), medical ultrasound (e.g., Ikeda et al. 2006; Pishchalnikov et al. 2011; Maxwell et al. 2011; Maeda et al. 2015; Movahed et al. 2016), surface cleaning 33 (Verhaagen & Rivas 2016; Yamashita & Ando 2019), chemical synthesis (Suslick et al. 1999; 34 Cairós & Mettin 2017), and bio-inspired devices (Tang & Staack 2019). Characterizing the 35 dynamics is a challenge due to the complex interactions of bubbles involving disorders and 36 stochasticity. Nuclei are typically micro-sized and polydisperse and randomly distributed. 37 38 Their rapid, nonlinear oscillations are, except in controlled experiments (Bremond et al. 2006), practically not measurable. Molecular and hydrodynamics simulations can provide 39 detailed insights into nucleation (Angélil et al. 2014; Gallo et al. 2021), while their time-40 and spatial scales have not reached those of practical cluster oscillations. Analyses have 41 been made on the interaction dynamics in various regimes (Brennen 2014), yet no common 42 43 knowledge has been established if the many-body coherence globally exists and if so scaling is possible, beyond the consensus that polydispersity induces strong disorders. 44

For the past decades, the Rayleigh-Plesset (R-P) equation and its variations have been 45 46 actively explored to investigate the dynamics of single bubbles (Plesset 1949; Plesset & Prosperetti 1977). Relatively few studies addressed the theory of clusters. By using mean 47 field approach to interacting bubbles modeled by the R-P equation, d'Agostino and Brennen 48 (d'Agostino & Brennen 1989) derived a nondimensional parameter that dictates the linear 49 50 coherent oscillations of monodisperse clusters, the so-called "cloud interaction parameter". Zeravcic et al. (2011) used the coupled R-P equations and identified disorders represented 51 by the Anderson localization of acoustic energy in polydisperse, lattice-like clouds under 52 weak excitation. We have recently extended the interaction parameter to the non-equilibrium, 53 cavitating clusters under strong excitation by considering the effective interaction at excited 54 55 states (Maeda & Colonius 2019; Maeda et al. 2018; Maeda & Maxwell 2021). To recall, we scale the mean kinetic energy of liquid induced by  $N(\gg 1)$  bubbles as (Maeda & Colonius 56 57 2019)

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$$\langle K \rangle \sim \langle K_s \rangle (1 + B_d), \tag{1.1}$$

where  $K_s$  is the energy of a single bubble:  $K_s = 2\pi\rho R_{h_c}^3 \dot{R}_{h_c}^2$ .  $B_d$  is the parameter controlling 59 the effective contribution of hydrodynamic inter-bubble interaction:  $B_d = N \langle \overline{R(t)} \rangle / R_C$ , and 60  $R_{b,c}$  and  $R_C$  denote the characteristic (reference) bubble radius and the cluster radius. 61  $\rho_l$  is the liquid density.  $\langle \cdot \rangle$  and  $\overline{\langle \cdot \rangle}$  denote time average during a period in which bubble 62 dynamics are statistically stationary and the mean value about the bubbles (i = 1, 2, ...N), 63 respectively. The scaling can be simply derived from the coupled R-P equation for the 64 correlated (synchronized) limit of monodisperse bubbles  $(R_1 = R_2 \cdots = R_{b,c})$ . Although 65 realistic correlations are imperfect due to polydispersity and nonlienarity,  $B_d$  was found to 66 control well both the coherent dynamics of polydisperse cavitating clusters and their acoustic 67 emission in numerical simulations and experiments (Maeda & Colonius 2019; Maeda & 68 Maxwell 2021). Overall, previous studies indicate that the coherence can depend on both 69 polydispersity and nonliearity in a non-separable manner, posing perplexing questions about 70 the universality of scaling. The theoretical characterization of the nonlinear dynamics of 71 disordered many-body systems is in general not a simple task. Meanwhile, greater computing 72 power has enabled learning physics by analysing big data. Principal component analysis 73 74 (PCA) is a powerful method for unsupervised learning which has seen recent success in characterizing the coherent physics of many-body and high-dimensional systems in fields 75 ranging from quantum information to fluid dynamics (Lloyd et al. 2014; Holmes 2012; Taira 76 et al. 2017; Milano & Koumoutsakos 2002). 77

In this study, we introduce and demonstrate a method for unsupervised data decomposition to study the coherent bubble cluster dynamics by combining theory and PCA. PCA extracts 80 dominant states and dynamical features, such as coherent quantum states and turbulent structures, and their amplitudes as the eigenfunction (feature) and the eigenvalue (variance) 81 of the co-variance matrix of physical data. When applied to spatio-temporal data of dynamical 82 systems, PCA is often denoted as proper-orthogonal decomposition (POD). Those data can 83 be properly weighted prior to PCA such that the variance becomes consistent with the 84 norm induced by an energetic inner product of state variables (e.g., kinetic energy) (Lall 85 et al. 1999; Rowley 2005). This weighting allows a physical interpretation that resulting 86 features associated with a large variance are energetically dominant coherent structures. 87 Proper weighting of Lagrangain bubble dynamics data is non-trivial since the linear variance 88 of extracted features need to account for the nonlinear interaction energy. For meaningful 89 analysis, we introduce strategic pre-processing of the data prior to PCA such that the PC-90 91 variance becomes theoretically consistent with the energy modeled by the coupled R-P equation. Analysing simulation data sets of clusters, we show that the PCA can systematically 92 extract not only coherent but also incoherent features whose magnitudes are respectively 93 measured by the PC-variance and the entropy. We discover that the coherence is lost by 94 disorders induced by polydispersity and nonlinearity, while under strong excitation the 95 underlying correlations are globally isolated in a single coherent feature whose variance 96 (energy) is scaled by  $B_d$ , regardless of the disorders. 97

The remainder of this paper is as follows. In §2, we describe the method. The first PC 98 variance, spectral entropy, and the coherence measure are introduced as quantifiable measures 99 100 to characterize the coherent bubble dynamics from extracted features. In §3, we verify and demonstrate the method using a numerical dataset of bubble clouds with different density and 101 polydispersity parameters under various amplitudes of harmonic excitation. The deviation 102 of the PC-variance from the physical energy is quantified for two weighting methods. The 103 amplitude dependencies of the measures are quantified. The PC-spectra and their correlations 104 with the coherent energy are analyzed. Moreover, the extracted coherent dynamics is related 105 106 to  $B_d$  and its universality is discussed for cavitating clouds. In §4, the physical significance of the method is discussed. In §5, we state conclusions. 107

#### 108 2. Methods

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#### 2.1. Principal component analysis of bubble dynamics data

For clusters modeled by the coupled R-P equations, observable dynamical variables are bubbles' radial velocities and radii. Consider a data matrix Q containing the  $N_t$  snapshots of

112 the radial velocities with a constant temporal interval:

113

$$\boldsymbol{Q} = [\boldsymbol{q}_1, \boldsymbol{q}_2, \dots, \boldsymbol{q}_{Nt}], \tag{2.1}$$

where  $q_k$  denotes the vector containing the radial velocities of the *N* bubbles at time  $t_k$  (in the *k*-th snapshot):

116  $\boldsymbol{q}_{k} = [\dot{R}_{1}(t_{k}), \dot{R}_{2}(t_{k}), \dots, \dot{R}_{N}(t_{k})]^{T}.$  (2.2)

For later convenience, we also define the vector  $\mathbf{r}_k$ , containing the radii of the bubbles at the same instances:

119

$$\boldsymbol{r}_{k} = [R_{1}(t_{k}), R_{2}(t_{k}), \dots, R_{N}(t_{k})]^{T}.$$
(2.3)

PCA can be performed on Q by using the singular value decomposition (SVD) (e.g., Abdi & Williams 2010; Jolliffe & Cadima 2016):

$$\boldsymbol{Q} = \boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{X}^*. \tag{2.4}$$

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123 The *i*-th principal component (feature) is stored in the *i*-th score matrix:

$$\Pi_i = U\Sigma_i,\tag{2.5}$$

125 where  $\Sigma_i$  contains the *i* – *th* largest singular value and zeros elsewhere.

#### 2.2. Weighted principal component analysis

Although this procedure for PCA is simple and straightforward, the physical meaning of the 127 extracted features are obscure since PCA itself is not informed on the underlying dynamics 128 of the system. A related issue of PCA for fluid flow data has been addressed in the context of 129 POD. In POD of the snapshots of Eulerian fluid flow data, the state vectors consisting the data 130 131 matrix are often weighted such that the corresponding weighted inner product of the state becomes consistent with the kinetic energy of the original system. The dominant features 132 (POD modes) can then be interpreted as energetically dominant coherent flow structures. 133 Moreover, in our previous studies (Maeda & Colonius 2019; Maeda & Maxwell 2021), the 134 scaling of bubble cloud dynamics by B was successfully demonstrated based on the total 135 kinetic energy of liquid induced by interacting bubbles. These considerations motivate us to 136 relate the energy with PCA for addressing the physics of bubble cloud. 137

Inspired by the POD, we consider weighting the present bubble dynamics data prior to PCA. To find an appropriate weight, we revisit the potential theory behind eq. (1.1). The kinetic energy of the fluid induced by the spherical bubble oscillations is explicitly expressed as

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$$K = 2\pi\rho_l \sum_{i=1}^{N} \left[ R_i^3 \dot{R}_i^2 + \sum_{j\neq i}^{N} \frac{R_i^2 R_j^2 \dot{R}_i \dot{R}_j}{r_{ij}} \right] + (H.O.T),$$
(2.6)

where  $R_i$ ,  $\dot{R}_i$ , and  $r_{ij}$  are the radius and the radial velocity of bubble *i*, and distance between the centers of bubble *i* and *j*, respectively. The second term in the bracket represents the contribution of the long-range interactions. At each instant, *K* can be expressed as a weighted inner product of *q*:

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$$K = \boldsymbol{q}^T \boldsymbol{T} \boldsymbol{q} = (\boldsymbol{W} \boldsymbol{q})^T (\boldsymbol{W} \boldsymbol{q}). \tag{2.7}$$

148 where

$$T_{ij}(\mathbf{r}_k) = \begin{cases} 2\pi\rho R_i^3(t_k) & (i=j), \\ 2\pi\rho \frac{R_i^2(t_k)R_j^2(t_k)}{r_{ij}}. & (i\neq j) \end{cases}$$
(2.8)

150 The weight matrix, W, can be obtained through the Cholesky factorization of T(r):

 $T(r) = WW^*.$ 

This expression suggests the weighted data, WQ, is appropriate for used in PCA. However, T(r) and W are time dependent since r can change in time during large-amplitude oscillations. The choice of  $r_k$  in the time series to define W is unclear. A straightforward choice is to use the temporal mean of the radius for each bubble,  $\langle r \rangle : \langle r \rangle = \sum_{k=1}^{Nt} r_k / Nt$ , but  $T(\langle r \rangle)$  is not a favorable approximation for T(r) for bubbles with large-amplitude oscillations.

We address this obstacle by variable transformation as a means of pre-processing the data. The schematic is shown in figure 1. First, we transform the variables from  $(\boldsymbol{q}, \boldsymbol{r})$  to  $(\boldsymbol{\xi}, \boldsymbol{\eta})$ , where  $\boldsymbol{\xi} = [\xi_1, \xi_2, ..., \xi_N]^T$  and  $\boldsymbol{\eta} = [\eta_1, \eta_2, ..., \eta_N]^T$ , and  $(\xi_i, \eta_i) = (q_i r_i, r_i) = (\dot{R}_i R_i, R_i)$ for  $i \in [1, N]$ .  $\xi_i$  is nothing but the velocity potential evaluated at the surface of bubble *i*. Supplemental discussions and justifications for this transformation are provided in Appendix

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Figure 1: Schematic of the feature extraction by PCA from Lagrangian bubble dynamics data, Q, after pre-processing. The variance of the resulting features is consistent with the interaction energy predicted by the coupled Rayleigh-Plesset equation.

163 A. The instantaneous energy of the system is expressed by a weighted inner product as

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$$K = \boldsymbol{\xi}^T \boldsymbol{P}(\boldsymbol{\eta})\boldsymbol{\xi} = (\boldsymbol{\Omega}\boldsymbol{\eta})^T (\boldsymbol{\Omega}\boldsymbol{\eta}). \tag{2.10}$$

165  $\Omega$  is the weight matrix satisfying

$$\boldsymbol{P}(\boldsymbol{r}) = \boldsymbol{\Omega}\boldsymbol{\Omega}^*, \tag{2.11}$$

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$$P_{ij}(\eta) = \begin{cases} 2\pi\rho\eta_i & i=j,\\ 2\pi\rho\frac{\eta_i\eta_j}{r_{ij}} & i\neq j. \end{cases}$$
(2.12)

169 Second, we partially replace  $\eta$  with  $\langle \eta \rangle$  to approximate the system. Using  $(\hat{\xi}, \hat{\eta})$ , the 170 instantaneous energy of the approximate system is expressed as

- 171  $\hat{K} = \hat{\boldsymbol{\xi}}^T \boldsymbol{P}(\hat{\boldsymbol{\eta}}) \hat{\boldsymbol{\xi}}.$  (2.13)
- 172 The temporal mean of the energy of the original system can then be approximated as

173 
$$\langle K \rangle \approx \langle \hat{K} \rangle = \langle \hat{\boldsymbol{\xi}}^T \boldsymbol{P}(\hat{\boldsymbol{\eta}}) \hat{\boldsymbol{\xi}} \rangle \approx \langle \boldsymbol{\xi}^T \boldsymbol{P}(\langle \boldsymbol{\eta} \rangle) \boldsymbol{\xi} \rangle.$$
(2.14)

This is a critical result in the present context of PCA, since the energy is now related to the weighted inner product with the constant weight,  $P(\langle \eta \rangle)$ . Quantitative verification of this approximation is addressed through numerical experiments in the following section. Using the new set of variables, the PC decomposition is performed as

$$\mathbf{\Omega} \mathbf{\Xi} = \boldsymbol{U}_{\boldsymbol{\xi}} \boldsymbol{\Sigma}_{\boldsymbol{\xi}} \boldsymbol{X}_{\boldsymbol{\xi}}^*. \tag{2.15}$$

The *i*-th PC is stored in  $\Pi_{\xi,i}$ :  $\Pi_{\xi,i} = U_{\xi} \Sigma_{\xi,i}$ . We denote the *i*-th largest singular value of  $\Sigma_{\xi}$  as  $\sigma_i$ . The degree of coherence can be measured by the normalized variance of the first PC:

 $\hat{\sigma}_1^2 = \sigma_1^2 / \operatorname{tr}(\boldsymbol{\Sigma}^2), \qquad (2.16)$ 

which represents the ratio of the energy occupied by the first PC to the total energy of the system. In the following sections, to distinguish the present method from the standard PCA, we denote (2.15) as the weighted principal component analysis of transformed data (WPCA-TD).

### 2.3. Spectral entropy and coherence measure

We introduce two additional key measures to characterize the coherent physics of bubble clusters through WPCA-TD. First, to quantify the degree of incoherent bubble oscillations,

#### we define the spectral entropy of the weighted co-variance matrix, $\Omega \Xi$ , as

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$$\hat{S}_{\nu N} = -\sum \frac{\hat{\sigma}_k^2 (\ln \hat{\sigma}_k^2)}{\ln(N)},$$
(2.17)

where  $\ln_2(N)$  is the normalization factor. The spectral entropy of data is a discrete analogue 193 194 of the Shannon entropy based on the spectrum of data and has been used to quantify the randomness of data in various applications (Kullback 1997; Alter et al. 2000; Hu et al. 2005; 195 De Domenico & Biamonte 2016). Aubry et al. (1991) introduced a similar definition of 196 entropy for spatio-temporal signals of canonical fluid flows from their POD eigenvalues and 197 used the entropy to characterize flow instabilities. In the present context, when bubbles are 198 in perfect correlation, we expect to excite only the first PC capturing the entire energy of the 199 system:  $\hat{\sigma}_1^2 = 1$  and  $\hat{\sigma}_k^2 = 0$  for  $k : k \in [2, N]$ , yielding  $\hat{S}_{\nu N} = 0$ . In contrast, if the energy is equi-partitioned into all PCs,  $\hat{\sigma}_k^2 = 1/N$  for all  $k : k \in [1, N]$  and  $\hat{S}_{\nu N} = 1$ . Second, we 200 201 define the coherence measure C. 202

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204 
$$C = \frac{B_1}{B_d},$$
 (2.18)

205 where

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 $B_1 = \frac{\sigma_1^2}{{\sigma_1'}^2} - 1. \tag{2.19}$ 

207  $\sigma_1^{\prime 2}$  is the first PC-variance excluding the contribution of interactions, obtained from the 208 WPCA-TD of the same data using a diagonal weight matrix  $\Omega'$  whose diagonal entries 209 are those of  $\Omega$ . Further details of  $\Omega'$  are provided in Appendix B. In the limit of perfect 210 correlation (also see eq. (1.1)),

$$\langle K \rangle \approx \sigma_1^2 \approx (1 + B_d) \sigma_1^{\prime 2} \tag{2.20}$$

212 and

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 $B_d \approx B_1. \tag{2.21}$ 

Therefore  $C \approx 1$ . This condition is typically realized in monodisperse clusters under weak (linear) oscillations (d'Agostino & Brennen 1989). For real clusters under strong excitation, bubbles are not perfectly correlated and the energy can be distributed in broad features. In this regime, approximation (2.20) is not necessarily expected to hold and *C* can take values far from unity. Phenomenologically speaking, *C* quantifies from data the degree to which the most coherent mode of oscillation is represented by the cluster's mean-field interaction. A schematic of the process to obtain *C* from data is provided in Appendix B.

#### 221 **3. Numerical experiments**

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#### 3.1. Data sets

To verify and demonstrate the WPCA-TD, we use data sets of spherical clusters excited by 223 40 cycles of harmonic pressure excitation. Each cluster contains  $O(10-10^3)$  bubbles with 224 their initial radii following log-normal distributions with a reference radius of  $R_{ref} = O(10)$ 225  $\mu$ m;  $\ln(R_0/R_{ref}) = N(0, s_d)$ , where  $s_d$  is the lognormal standard deviation as the measure 226 of polydispersity (Maeda & Colonius 2019). We address  $s_d = [0.1, 0.3, 0.5, 0.7]$ . In real 227 bubble clouds, nuclei are expected to be polydisperse.  $s_d = 0.7$  may be a representative 228 estimation based on previous studies (Katz 1978; Ando et al. 2012; Maeda & Colonius 229 230 2019), and is used unless noted. The smaller values of  $s_d$  are used in some cases to quantify the effect of polydispersity. The bubbles are randomly distributed in the spherical region 231



Figure 2: Evolution of representative quantities of a bubble cloud with  $(B_0, s_d, N) = (0.5, 0.1, 100)$  excited at A = 20, during a stationary state. (a) Radius of a representative bubble. (b) For the same bubble,  $\xi$  obtained from the raw data, and those from the first and second dominant features extracted using WPCA-TD. (c) Void fraction. (d) Kinetic energy of the fluid induced by the bubble cloud.

with a specified cluster radius. Similar parameters of clusters were previously simulated to 232 compare with experiments (Maeda & Colonius 2019; Maeda & Maxwell 2021). The density 233 of bubbles is characterized by  $B_0$ , the value of  $B_d$  at rest. The far-field pressure is given 234 as  $p_{\infty}(t) = p_0[1 + A\sin(2\pi ft)]$ . The frequency of excitation is f = 500 kHz unless noted, 235 near the adiabatic resonant frequency of the reference bubble. The amplitude of excitation is 236 defined by A, relative to the ambient pressure at  $p_0 = 1.0$  atm. For each set of parameter, we 237 compute an ensemble average by taking a mean of the results from 20 bubble clouds with 238 distinct spatial placements of bubbles in the clouds. For data generation, we use mesh-free, 239 coupled Keller-Miksis equations by modifying previous methods. Details of this method are 240 provided in Appendix D. 241

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#### 3.2. Visualization of representative data

In figure 2 we show evolution of representative quantities of a bubble cloud in the dataset with  $(B_0, s_d, N) = (0.5, 0.1, 100)$  excited at A = 20, during a stationary. Figure 2 (a) shows the radius of a representative bubble. The plot presents familiar features of cavitation



Figure 3: Projected side-views of the three-dimensional bubble cloud of figure 2The size of the spheres denotes the root-mean-square amplitude of the velocity potential evaluated at the bubble surface at corresponding locations during the stationary state of oscillations, for (a) the raw data, (b) the first principal feature, and (c) the second principal feature.

246 bubbles forced by continuous, strong excitation, including fast events of collapse/rebound and slow growth/decay between them. During the slow phase, small-amplitude oscillations at 247 excitation amplitude are evident. For the same bubble, figure 2(b) shows the evolution of the 248 velocity potential obtained from the raw data, and those from the first and second dominant 249 features extracted through the WPCA-TD. Compared to the radius, the raw data of the 250 velocity potential looks much more symmetric about zero, even around the collapse events. 251 The potential of the first feature presents a sinusoidal profile at the excitation frequency 252 and with a constant amplitude which is close to the peak amplitude of the original data. 253 The collapse events are not captured in this feature. The potential of the second feature 254 is symmetric but has a much lower amplitude compared to the first feature. There is no 255 clear similarity between the original data and the second feature, unlike that between the 256 original data and the first-PC. Figure 2(c) shows the void fraction. The fraction oscillates 257 with an amplitude of around  $5.0 \times 10^{-4}$  near  $3.0 \times 10^{-3}$  at the excitation frequency. Slow, 258 small amplitude of variations are also observed. Figure 2(d) shows the kinetic energy of 259 fluid induced by bubble oscillations. The energy oscillations around 0.75  $\mu$ J at doubled 260 the excitation frequency. Although the frequency is as expected, the peak amplitude largely 261 fluctuates in the window as well as the waveform is not symmetric, unlike the void fraction. 262 The fluctuation and asymmetry indicate can be associated with the incoherent oscillations to 263 the kinetic energy. For instance, if one bubble is expanding and another bubble is collapsing 264 out of phase, their net contribution may not appear in the void fraction due to mutual 265 cancellation but can appear in the energy. Overall, the averaged quantities, void fraction and 266 the energy, are much smoother than the individual bubble dynamics. This can be trivially 267 explained by the incoherence of violent collapse events among bubbles and coherence of 268 the linear response against fundamental frequencies. Meanwhile, the quantitative nature of 269 coherent response is not predictable or easily analyzable from these plots due to strong 270 non-linearity, especially under inter-bubble interactions with disordering factors including 271 randomness of bubble position and polydispersity. 272

Figure 3(a-c) show the projected side-views of the three-dimensional bubble cloud of figure 2. The size of the spheres denotes the root-mean-square amplitude of the velocity potential evaluated at the bubble surface at corresponding locations during the stationary state of oscillations, for (a) the raw data, (b) the first principal feature, and (c) the second principal feature. The size of spheres can be interpreted as the mean energy of oscillations of bubbles at those locations in each feature. The overall distribution of the spheres of the



Figure 4: Relative error of the mean kinetic energy of the fluid induced by clusters for the two approximations,  $(\times):\langle K \rangle \approx \langle q^T T(\langle q \rangle)q \rangle$  and  $(\circ):\langle K \rangle \approx \langle \xi^T P(\langle \eta \rangle)\xi \rangle$ , against the excitation pressure amplitude with various polydispersities and values of  $B_0$ . Black:  $(s_d, B_0) = (0.1, 0.5)$  and red:  $(s_d, B_0) = (0.7, 5.0)$ .

1st feature resembles that of the raw data, while the energy of the bubbles in the 2nd feature is much smaller than that of the 1st feature. The plots therefore visually confirm that the 1st-feature represents the most energetic mode of oscillations in the original data. This result also agrees with the observation of figure 3(b).

#### 3.3. Error analysis

To show the effectiveness of the pre-processing, in figure 4, we plot the relative errors of the time-averaged kinetic energy of bubble clusters, one approximated using the original variable  $(\langle q^T T(\langle r \rangle) q \rangle)$  and the other using the transformed variables  $(\langle \xi^T P(\langle \eta \rangle) \xi \rangle)$ , against the excitation amplitude. At  $A < 10^{-1}$ , the error is nearly zero for both approximations. At  $A > 10^{-1}$ , at which bubble dynamics become nonlinear, the error grows with A for the former, while it remains small for the latter. This result confirms the improved approximation by the pre-processing.

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#### 3.4. Amplitude dependence of the key measures

The coherent dynamics critically depend on the excitation amplitude. Figure 5 shows the 292 dependence of  $\hat{\sigma}_1^2$ ,  $\hat{S}_{\nu N}$ , and C against A for various density and polidispersity parameters 293 of clouds. This dependence is best highlighted in the result of sparse, weakly polydisperse 294 cluster ( $B_0 = 0.5, s_d = 0.1$ ) in figure 5(a). The relative importance of the first PC,  $\hat{\sigma}_1^2$ , 295 decays nearly monotonically from 0.9 to 0.2 through three distinct regimes. For  $A \leq 0.2$ ,  $\hat{\sigma}_1^2 \approx 1$  meaning the entire energy is captured by the first PC. Then  $\hat{\sigma}_1^2$  rapidly decays to 0.4 and stays nearly constant up to  $A \approx 3$ . At A > 3,  $\hat{\sigma}_1^2$  decays again and stay nearly constant 296 297 298 around 0.2. The decay indicates the decrease in the coherence with increasing A and can be 299 explained by the excitation of the nonlinear oscillations and cavitation triggered at  $A \approx 1$ and above.  $\hat{S}_{vN}$  has a profile vertically mirrored to  $\hat{\sigma}_1^2$ ;  $\hat{S}_{vN}$  increases from around 0.1 to 300 301 0.5 through the three regimes, indicating more partitioning of the energy into multiple PCs 302 and increase of incoherence, by increasing A. The mirrored profiles of  $\hat{\sigma}_1^2$  and  $\hat{S}_{\nu N}$  suggest 303 304 that these parameters are complementary. 305



Figure 5: The first PC-variance  $(\hat{\sigma}_1^2)$ , the normalized von Neumann entropy  $(\hat{S}_{\nu N})$ , and the coherence measure (*C*), against the excitation amplitude with various initial density and polydispersity parameters, with  $(B_0, s_d) = (a) (0.5, 0.1)$ , (b) (0.5, 0.7), (c) (5.0, 0.1), and (d) (5.0, 0.7).

Remarkably, C draws a square-well like profile, where  $C \approx 1$  for both low (A < 0.2) and 306 large (A > 5) amplitudes reaching a minimum value  $(C \approx 0.5)$  at  $A \approx 1$ . This counter-307 intuitive result suggests that the energy of the first PC is scaled by the mean-field parameter 308  $B_d$  regardless of the increase of incoherence for large A, and the scaling is lost only for the 309 intermediate range at 1 < A < 5. Comparisons with the result of dense, weakly polydisperse 310 clusters  $(B_0, s_d) = (5.0, 0.1)$  shown in figure 5(b) highlights the effect of the density of bubbles. In figure 5(b),  $\hat{\sigma}_1^2$  takes values near unity at small A and decays at  $A \approx 1.0$  to around 311 312 0.4 and stays nearly constant at A > 5.0. At A > 10,  $\hat{\sigma}_1^2$  slightly grows against A.  $\hat{S}_{\nu N}$  has a profile vertically mirrored to  $\hat{\sigma}_1^2$ . The features of  $\hat{\sigma}_1^2$  and  $\hat{S}_{\nu N}$  are similar to those observed in figure 5(a), except that the transition occurs at a larger range of A. The sudden decay and 313 314 315 growth of  $\hat{\sigma}_1^2$  and  $\hat{S}_{\nu N}$  can likewise be associated the linear-to-nonlinear transition of bubble 316 dynamics which results in incoherence. Meanwhile, the positive shift of the transition range 317 of A indicates that the dense bubble clouds tend to behave more coherently than sparse bubble 318 clouds, agreeing with the previously theory (d'Agostino & Brennen 1989; Maeda & Colonius 319 320 2019). C is greater than 0.5 at almost all values of A, and is relatively more insensitive against A compared to figure 5(a), indicating that the cluster dynamics is moderately controlled by 321

 $B_d$ . Figure 3(c) and (d) respectively corresponds to sparse and dense clusters with strongly 322 polydisperse nuclei;  $(B_0, s_d) = (0.5, 0.7)$  and (5.0, 0.7). These plots show clear differences 323 from those of weekly polydisperse clusters in figure 5(a) and figure 5(b). For the sparse 324 clusters (figure 5(c)),  $\hat{\sigma}_1^2$  mildly decays from 0.8 to 0.7 at 0.1 < A < 0.2, sharply decays to 325 the minimum of 0.2 at  $A \approx 0.4$  and then mildly grows to 0.3 at A = 1.2. The sharp decay 326 resembles that in figure 5(b), while the slope is milder.  $\hat{S}_{\nu N}$  has also a profile mirrored to 327  $\hat{\sigma}_1^2$ , but it is less symmetric than figure 5(a) and figure 5(b).  $\hat{S}_{\nu N}$  is nearly constant around 328 0.2 at 0.1 < A < 2.0 and draws a concave curve with its maximum of around 0.5 at  $A \approx 5.0$ 329 followed by a smooth decay to 0.3 at A = 20. C almost constantly increases from 0.2 to O(1)330 throughout the plot, indicating that the coherent dynamics is controlled by  $B_d$ , only at large 331 A, unlike weakly polydisperse case of figure 5(a). The overall trend of the plots in figure 5(b)332 333 is similar to figure 5(a), although the changes of variables against A are milder in figure 5(b). Overall, the mutual trends of variables at A > 5 are similar between figure 5(a) and 5(c) and 334 between figure 5(b) and 5(d), indicating the decreasing influence of the initial polydispersity 335 in the nonlinear regime. At A < O(1), the polydisperse clouds tend to have smaller values of 336  $\hat{\sigma}_1^2$ , and larger values of  $\hat{S}_{vN}$  and  $\hat{C}$ . This can be explained by the enhancement of incoherent 337 dynamics induced by polydispersity. 338

339

#### 3.5. Principal component spectrum

To gain deeper insights on the meaning of C, in figure 6(a-d) we show the PC-variances 340 obtained at  $A = 2 \times 10^{-2}$ , 1.2, and 20, for the first 10 PCs, obtained from the sparse, 341 weakly polydisperse clouds blueplotted in figure 5(a). The insets show the evolution of the 342 square-root of the normalized total energy ( $\sqrt{K}$ ) and those of the first and the second PC-343 variances ( $\sqrt{K_1}$  and  $\sqrt{K_2}$ ), during the four periods of excitation in statistically stationary 344 states. As expected, in the linear regime (figure 6(a), the first PC occupies nearly the entire 345 energy.  $\sqrt{K_1}$  evolves at the fundamental frequency. In the transition regime (figure 6(b)), the 346 first PC occupies 40% of the energy and the rest is partitioned into the sub-dominant PCs 347 with a smooth decay.  $\sqrt{K}$  evolves more chaotic than the linear regime, as expected due to 348 the nonlinear response of bubbles. Both  $\sqrt{K_1}$  and  $\sqrt{K_2}$  evolve with similar quasi-periodic 349 profiles. We interpret that both PCs represent the coherent part of the energy. 350

Interestingly, in the nonlinear regime (figure 6(c)) energy partitioning is non-smooth; the 351 first PC occupies 40% of the total energy similar to the transition regime, but the rest of the 352 energy is broadly distributed into the other PCs with much smaller amplitudes. The evolution 353 of  $\sqrt{K}$  is non-periodic with noisy, fine structures of spikes. These spikes are expected due 354 to the incoherent collapse events. The evolution of  $\sqrt{K_1}$  is, in contrast, highly periodic, and 355 somewhat resembles that of figure 6(b). The evolution of  $\sqrt{K_2}$  is more chaotic and less 356 smooth than  $\sqrt{K_1}$ . The difference between the first-PC and the rest of PCs suggest that, in this 357 regime, only the first PC captures a major coherent feature and the rest of PCs represent more 358 359 the incoherent dynamics as broadband noise. Figure 6(d) shows the result of the nonlinear regime with a stronger excitation amplitude (A = 20). Overall, both the spectrum and the 360 evolution of K look similar to that of figure 6(c), other than that the amplitude of the first 361 PC-variance is increased to 60%. The resemblance of figure 6(c) and figure 6(d) indicates 362 that the dynamical features identified from these two plots are common in the non-linear 363 regimes. 364

The resemblance of the evolution of the first PCs in the linear and the nonlinear regimes can explain the recovery of *C* at A > 5 in figure 6(a). Although the overall dynamics are much more chaotic in the nonlinear regime, the contribution of the coherent interactions to the system's energy effectively appears only in the first PC in both regimes and therefore the relative contribution of the interaction to the first PC is commonly scaled by  $B_d$ . This result



Figure 6: (a-d) The PC spectral profiles at  $A = 2 \times 10^{-2}$ , 1.2, 8.6, and 20. Insets show the evolution of the square-root of the normalized total energy ( $\sqrt{K}$ , black) and those of the first (blue) and the second (red) PC-variances ( $\sqrt{K_1}$  and  $\sqrt{K_2}$ ), during the four periods of harmonic excitation, with  $\hat{t}$  being a non-dimensional time  $\hat{t} = tf$ . The y-axis of each inset is normalized by the maximum value of  $\sqrt{K}$ .

also implies that the underlying coherence in the nonlinear regime represents the perfectcorrelation (synchronized oscillations) like that of linear, monodisperse clouds.

#### 3.6. Evaluation of the coherence measure

To assess the variation of the coherence measure dependent on the three regimes, in figure 373 7(a-c) we plot  $B_1$  against  $B_d$  for  $O(10^3)$  clusters with various values of  $s_d$ , N, and  $R_C$ , at the three distinct excitation amplitudes ( $A = 2 \times 10^{-2}$ , 1.2, and 20). Appendix D summarizes the 374 375 376 parameters used. With the weak excitation (figure 7(a)), bubble oscillations are in a linear regime and  $B_d \approx B_0$ . The data points are collapsed on the line of C = 1 for  $s_d = 0.1$ , while 377 data points are scattered for the other values of  $s_d$ . This result is expected as  $B_d$  was originally 378 defined to scale the coherence of the monodisperse, perfectly correlated bubbles in the linear 379 regime (d'Agostino & Brennen 1989; Zeravcic et al. 2011). With the intermediate excitation 380 381 (figure 7(b)), the bubble oscillations are nonlinear. The data points are scattered from C = 1, regardless of the value of  $s_d$ . In this regime, the result indicates that the coherence is lost due to 382

372



Figure 7:  $B_1$  against  $B_d$ , for  $O(10^3)$  clusters with various values of  $s_d$ , N,  $R_C$ , and other physical parameters (Appendix D) in the linear (a:  $A = 2 \times 10^{-2}$ ), transition (b: A = 1.2), and nonlinear (c: A = 20) regimes.

the nonlinear dynamics, regardless of polydispersity. Surprisingly, with the strong excitation, 383 (figure 7(c)), the data points are collapsed on the line of C = 1, meaning that the variance of 384 the first PC is scaled by  $B_d$ , regardless of the parameters. This collapse is not observed for the 385 second PC, regardless of the parameters (Appendix E). The results suggest that the scaling 386 of  $B_1$  is universal for cavitating clusters, which are typically excited at O(1) MPa and above. 387 Physically speaking, the scaling indicates that in cavitating clusters, the energy is partitioned 388 into a single coherent mode of correlated (synchronized) oscillations and incoherent modes 389 generalizing the aforementioned interpretation of figure 6(c) and figure 6(d). The coherent 390 energy is controlled by the mean field originally derived for monodisperse, near-equilibrium 391 bubbles. It is suggested that this partitioning and scaling are universal regardless of nuclei's 392 polydispersity and the degree of nonlinearity. This finding explains successful use of  $B_d$  in 393 characterizing and controlling seemingly disordered clusters in our previous studies (Maeda 394 & Colonius 2019; Maeda & Maxwell 2021). The isolation of coherence implies that the 395 396 details of the microscopic scale as well as of the many-body interactions represented by higher-order PCs could be modeled as fast variables, which force the macroscopic (relevant) 397

scales in the form of noise. A rigorous way to corroborate this hypothesis might be the Mori-Zwanzig projection operator formalism (Mori 1965) by assuming that the fluctuations of fast and slow variables are uncorrelated. Although the choice of relevant slow variables may be unclear, the present approach is promising since the WPCA-TD can be seen as a prompter for more refined models of the evolution of slow variables.

## 403 **4. Significance of the WPCA-TD to inform on cavitation physics**

In general, PCA can be considered a mathematical technique for data decomposition, 404 and the physical meaning of extracted features can be left to one's interpretation. To the 405 authors' knowledge, studies of complex fluid flows employing data decomposition and feature 406 extraction techniques often rely on one's intuition to discuss the physical meaning of features. 407 In fact, in §3.5, the analyses of the PC spectra required rigorous interpretations based on 408 previous knowledge on cavitation physics. Meanwhile, the correlation between  $B_1$  and  $B_d$ 409 identified in the last section shows that the present WPCA-TD can directly extract  $B_d$  from 410 data without additional signal processing like spectral filtering, which are often required for 411 Fourier-based analysis, despite the presence of noisy and incoherent features. To generalize, 412 WPCA-TD is not only a tool for data decomposition and feature extraction but also can be 413 used to directly inform on the non-dimensional number that controls the coherent physics 414 of interests. This informative aspect of the WPCA-TD can provide a meaningful shortcut to 415 address the physics of cloud cavitation. 416 To perform WPCA-TD, bubble dynamics data can be obtained from experimental mea-417

surements as well as other numerical approaches (e.g., Kameda & Matsumoto 1996; Maeda 418 & Colonius 2018; Pishchalnikov et al. 2019). The cluster's shape can be arbitrary. Although 419 bubble's translation and deformation are neglected in the present numerical experiments, 420 WPCA-TD can incorporate dynamical variables controlling these effects (e.g., Ilinskii et al. 421 2007; Murakami et al. 2020). Physically meaningful data decomposition requires the fine 422 temporal resolution of individual bubble dynamics. In practice, such information would be 423 difficult to obtain in experiments except for a small number of bubbles in a highly controlled 424 environment. We thus emphasize that WPCA-TD would primarily be useful to process fine 425 temporal resolution of numerical data. 426

#### 427 **5. Conclusion**

In conclusion, to corroborate the coherent dynamics of bubble clusters, we introduced and 428 demonstrated WPCA-TD, a method of PCA to comprehensively decompose the time series 429 of Lagrangian bubble dynamics data into coherent dynamical features, in way similar to 430 the modal decomposition of Eulerian flow field data. The data are pre-processed such that 431 the PC-variance of the features becomes consistent with the hydrodynamic potential energy 432 induced by bubble oscillations that is predicted by the R-P equation. Analyzing simulation 433 data sets of clusters under harmonic excitation, we demonstrated that the coherent energy and 434 the degree of incoherence are respectively quantified by the variance and the spectral entropy. 435 The coherence was lowered by disorders induced by nuclei's polydispersity and nonlinear 436 response of bubbles, as expected. Meanwhile, in cavitating regimes, underlying, correlated 437 mode of oscillations were isolated in a single dominant feature. The variance of this feature 438 was found to be controlled by the previously identified mean-field parameter,  $B_d$ , regardless 439 of the disordering factors, indicating that the underlying coherent dynamics may be universal 440 in cavitating clusters. These results suggest that the method can provide a simplified and 441 442 comprehensive representation of complex bubble dynamics. Analogous to the use of POD for reduced-order modeling (ROM) of various flows, the dynamical features extracted by 443

PCA may be used for ROM, without directly solving many-body interactions. Such a model
may be promising for controlling cavitation and nucleation without tracking individual nuclei.

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450

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# 465 Appendix A. Variable transformation for a single bubble

In this section, we provide supplemental discussions and justification on the variable transformation used in the WPCA-TD, by considering the single bubble dynamics. By transformation  $(\xi, \eta) = (R\dot{R}, R)$ , with  $\xi$  being nothing but the velocity potential evaluated at the bubble surface, the R-P equation can be expressed as

$$\dot{\xi} = -\frac{1}{2} \left(\frac{\xi}{\eta}\right)^2 + \frac{p_b - p_\infty(t)}{\rho},\tag{A1}$$

470

 $\dot{\eta} = \frac{\xi}{n}.\tag{A2}$ 

472

473  $p_b$  and  $p_{\infty}$  are the pressure inside the bubble and that in infinity, respectively. The 474 instantaneous energy of the system is expressed as

475 
$$K = 2\pi\rho \dot{R}^2 R^3 = 2\pi\rho \xi^2 \eta.$$
 (A 3)

Next, we approximate the system (A 1). Given the time series data, the temporal average of  $\eta$  can be computed as  $\langle \eta \rangle$ . Using  $\langle \eta \rangle$ , we approximate the system of eq. (A 1) on a space spanned by a set of new variables  $(\hat{\xi}, \hat{\eta})$ .

479 
$$\dot{\hat{\xi}} = -\frac{1}{2} \left( \frac{\hat{\xi}}{\langle \eta \rangle} \right)^2 + \frac{p_b - p_{\infty}(t)}{\rho}, \tag{A4}$$

This system models well the dynamical features of the R-P equation including bifurcation, although  $\hat{\xi}$  and  $\hat{\eta}$  are now partially decoupled. Our explanation is the following. In the linear regime, the quadratic term of eqn. (A 4) can be neglected, and this system becomes



Figure 8: Comprehensive schematic of the present procedure to obtain the spectral entropy, PC-variance, and coherence measure, from input data.

identical with the original one. In nonlinear, cavitating regime, the bubble size  $(\eta)$  varies slowly near its peak after the explosive cavitation growth. Sporadic, fast collapse events do not influence much the temporal mean of the bubble size. Therefore,  $\eta$  is close to  $\langle \eta \rangle$ except at collapse events and, even if  $\eta$  changes rapidly during the collapse and rebound, this change has a relatively small influence on the mean behavior of the system at the timescale of (statistically) stationary bubble oscillations.

491 We can express the instantaneous energy of this approximate system as

492

$$\hat{K} = 2\pi\rho\hat{\xi}^2\hat{\eta}.\tag{A6}$$

With the same initial condition ( $\xi = \hat{\xi}$  and  $\eta = \hat{\eta}$  at t = 0), the temporal mean of the energy of the original system is approximated as

$$\langle K \rangle \approx \langle \hat{K} \rangle = 2\pi\rho \langle \hat{\xi}^2 \hat{\eta} \rangle \approx 2\pi\rho \langle \hat{\xi}^2 \rangle \langle \eta \rangle. \tag{A7}$$

495 496

497 Note that Preston *et al.* (2007) used a POD-based analysis of single bubble dynamics for 498 reduced-order modeling of heat and mass diffusion across bubble interface. In the study, the 499 temperature and concentration fields were obtained by solving partial differential equations 500 and then represented by POD modes, following the POD/Galerkin framework. This is distinct 501 from the present PCA (POD) of Lagrangian bubble dynamics data based on the direct 502 transformation and projection of the Rayleigh-Plesset equation.

#### 503 Appendix B. Schematic of the input-output procedure

504 Figure 8 shows the schematic of the present procedure to obtain the spectral entropy, PC-

variance, and coherence measure, from the input data including the time series of the radius and radial velocity of Lagrangian bubbles.

For computing *C*, we introduced the alternative weight,  $\Omega'$ .  $\Omega'$  is defined through P':  $P'(\langle s \rangle) = \Omega' \Omega'^*$ , where P' is the diagonal matrix with its entries from P:

509 
$$P'_{ij}(\eta) = \begin{cases} 2\pi\rho\eta_i & i=j, \\ 0 & i\neq j. \end{cases}$$
(B1)

The corresponding inner product,  $\boldsymbol{\xi}^T \boldsymbol{P}' \boldsymbol{\xi}$ , represents the portion of the energy of the system excluding the contribution of inter-bubble interactions.

512 
$$K' = \boldsymbol{\xi}^T \boldsymbol{P}' \boldsymbol{\xi}, \tag{B 2}$$

$$K' = 2\pi\rho_l \sum_{i=1}^{N} R_i^3 \dot{R}_i^2 + (H.O.T).$$
 (B 3)

514 515

## 516 Appendix C. Details of the K-M equation used for data preparation

In this section, we provide details of the formulation of the Keller-Miksis (K-M) equation for 517 multiple bubbles, which is used to generate the Lagrangian bubble dynamics data. Various 518 extensions of the Rayleigh-Plesset equation and its applications to a system of multiple 519 bubbles are available (Doinikov 2004; Takahira et al. 1994; Ilinskii et al. 2007; Yasui et al. 520 2008). Our formulation can be derived from the K-M equation extended for multiple bubbles. 521 522 First, we recall the general formulation for the oscillations of interacting spherical bubbles in weakly compressible liquid with arbitrary inter-bubble distances, whose derivation is, for 523 instance, provided in Appendix 2.4 of Fuster & Colonius (2011). In the present study, we 524 use a simplified version of this derivation. To recall, in Fuster & Colonius (2011), the radial 525 evolution of bubble *i* is described as 526

527 
$$\ddot{R}_{i}\left(R_{i}\left(1-\frac{\dot{R}_{i}}{c}\right)\right) + \frac{3}{2}R_{i}^{2}\left(1-\frac{\dot{R}_{i}}{3c}\right) = F^{*} + I^{*}, \qquad (C1)$$

where  $F^*$  and  $I^*$  represent the forcing due to the external potential and the inter-bubble interaction, respectively, and are expressed as

530 
$$F^* = \frac{\partial \phi_{\infty}}{\partial t} \left( 1 - \frac{\dot{R}_i}{c} \right) + \frac{R_i}{c} \frac{\partial^2 \phi_{\infty}}{\partial t^2} + H_i \left( 1 + \frac{\dot{R}_i}{c} \right) + \frac{R_i \dot{H}_i}{c}, \quad (C2)$$

531 and

532 
$$I^* = \sum_{j \neq i}^{N} \left[ \left( 1 + \frac{\dot{R}_i}{c} \right) \frac{\partial \phi_j(R_i)}{\partial t} \right] + \frac{R_i}{c} \sum_{j \neq i}^{N} \left[ \left( 1 + \frac{\dot{R}_j(t')}{c} \right) \left( 1 - \frac{\dot{R}_j}{c} \right) \frac{\partial^2 \phi_j(t' - R_j(t')/c)}{\partial t'^2} \right]$$
(C 3)

$$\sum_{j \neq i}^{533} - \sum_{j \neq i}^{N} \left[ \left( 1 + \frac{\dot{R}_j(t')}{c} \right) \frac{\partial \phi_j(t' - R_j(t')/c)}{\partial t'} \frac{R_i}{R_j} \frac{\dot{R}_j}{c} \right].$$
 (C4)

 $\phi_{\infty}$  is the velocity potential of liquid at infinity, and  $\phi_i(R_i)$  and  $H_i$  are the potential and the enthalpy of liquid evaluated at the surface of bubble *i*. *t'* is the retarded time defined as  $t' = t - (d_{ij} - R_j)/c$ , where  $(d_{ij} - R_j)/c$  represents the travel time for the pressure wave to reach bubble *i* from the surface of the bubble *j* and  $d_{ij}$  is the distance between the centers of those bubbles. In the sparse limit, the equation recovers the original Keller-Miksis equation (Keller & Miksis 1980).

To close the equations, several relations are considered. Using the Bernoulli's equation, the potential for the bubble i can be expressed as

543  
544
$$\frac{\partial \phi_i(R_i)}{\partial t} = -\left(\frac{1}{2}\dot{R}_i^2 + H_i + \sum_{j \neq i}^N \frac{\partial \phi_j(R_i)}{\partial t} + \frac{\partial \phi_\infty}{\partial t}\right).$$
(C5)

18

545 The velocity potentials at the bubble i and bubble j satisfy the following relation.

$$\frac{\partial \phi_i(R_i)}{\partial t} = \frac{R_j(t')}{d_{ij}} \frac{\partial \phi_j(t' - R_j/c)}{\partial t'}.$$
 (C6)

548 The enthalpy and the potential derivative are approximated as

$$H_i \approx \frac{p_i - p_0}{\rho_{l,0}}.\tag{C7}$$

549 550

560

551 
$$\frac{\partial \phi_{\infty}}{\partial t} \approx \frac{p_{\infty} - p_0}{\rho_{l,0}}.$$
 (C 8)

Finally,  $p_{\infty}$  is obtained using the information of the background Eulerian field computed on a mesh.

In the present study, we simplify  $F^*$  and  $I^*$  by invoking further approximations. First, consider that the bubble cluster size is smaller than the characteristic length-scale of the pressure wave in the field,  $\lambda_c$ . The inter-bubble distance in the cluster is naturally smaller than  $\lambda_c$ :

$$d_{ij} - R_j \ll \lambda_c. \tag{C9}$$

559 Dividing both sides with c,

$$\frac{d_{ij} - R_j}{c} = t - t' \ll \frac{\lambda_c}{c} = \frac{1}{f_c} = T_c,$$
 (C10)

(C12)

where  $f_c$  and  $T_c$  are the characteristic frequency and the period of the wave in the field. Therefore, the difference between *t* and *t'* is much smaller than the characteristic timescale of the dynamics. Given this knowledge, we approximate that  $t' \approx t$ . Second, we neglect the terms in the order of  $(\dot{R}/c)^2$ . Using these approximations, we can simplify  $F^*$  and  $I^*$  as

565 
$$F^* = \frac{p_i - p_\infty}{\rho_l} \left( 1 + \frac{\dot{R}_i}{c} \right) + \frac{R_i}{\rho_l c} \frac{\partial(p_i - p_\infty)}{\partial t}$$
(C11)

566 and

567 
$$I^* =$$

$$568 - \sum_{j \neq i}^{N} \frac{R_j}{d_{ij}} \left( \frac{1}{2} \dot{R}_j^2 + \ddot{R}_j \left( R_j \left( 1 - \frac{\dot{R}_j}{c} \right) \right) + \frac{3}{2} \dot{R}_j^2 \left( 1 - \frac{\dot{R}_j}{3c} \right) - \frac{p_j - p_{\infty}}{\rho_l} \frac{\dot{R}_j}{c} - \frac{R_j}{\rho_l c} \frac{\partial (p_j - p_{\infty})}{\partial t} \right).$$

$$(C 13)$$

569

571

570 For harmonic excitation,

 $p_{\infty} = p_a \sin(\omega t). \tag{C14}$ 

572 We use polytropic law to describe the pressure of the gas inside each bubble (Brennen 2014).

573 
$$p_i = p_{i,0} \left(\frac{R_{i,0}}{R_i}\right)^{3\gamma},$$
 (C15)

where  $\gamma$  is the constant polytropic exponent. Eqns (C 1), (C 11) and (C 13), together with relations (C 14) and (C 15) provide a complete system of ODEs for the radius of *N* interacting

576 bubbles, which can be readily solved with a given initial condition.

N 16 32 64 128 256 512	<i>R<sub>c</sub></i> [mm] 0.33-2.0 0.33-2.0 0.33-2.0 0.33-2.0 0.33-2.0 0.8-2.0	$R_{ref}$ [µm] 10 10 10 10 10 10	<i>sd</i> 0.1-0.7 0.1-0.7 0.1-0.7 0.1-0.7 0.1-0.7 0.1-0.7	f [kHz] 500 500 500 500 500 500	N 16 32 64 128	<i>R<sub>c</sub></i> [mm] 0.33-2.0 0.33-2.0 0.33-2.0 0.33-2.0	$R_{ref}$ [µm] 10 10 10 10	<i>s<sub>d</sub></i> 0.1-0.7 0.1-0.7 0.1-0.7 0.1-0.7	f [kHz] 500 500 500 500
512 64	0.33-2.0 0.33-2.0	10 10 5	0.1-0.7 0.1-0.7 0.1-0.7	500 500 500	128	0.33-2.0	10	0.1-0.7	500
64	0.33-2.0	10	0.1-0.7	250					

Table 1: Summary of the parameters used for the data set of clusters analyzed in the main manuscript.

#### 577 Appendix D. Summary of the parameters

578 Table 1 summarizes a set of parameters used to construct the database analyzed the main

579 manuscript. The number of bubbles N, cluster radius  $R_c$ , reference bubble radius  $R_{ref}$ ,

polydispersity measure  $s_d$ , and the forcing frequency were varied. The left table of parameters are used for the clusters in figure 4 ( $s_d = 0.1, 0.7$ ), figure 7(a) (all values of  $s_d$ ), and figure

are used for the clusters in figure 4 ( $s_d = 0.1, 0.7$ ), figure 7(a) (all values of  $s_d$ ), and figure 9(a) (all values of  $s_d$ ). The right table of paramters are used for the clusters in figure 7 (b),

583 figure 7 (c), figure 9 (b), and figure 9 (c).

#### 584 Appendix E. Scaling of the second PC

Figure 9 shows the scaling of the interaction energy of the second dominant feature of bubble clouds in the data set,  $B_2 = \sigma_2^2/\sigma_2'^2 - 1$ , for various values of excitation amplitude and nuclei polydispersity. For all parameters, data points are widely scattered and there is no clear correlation observed between  $B_2$  and  $B_d$ , indicating that the second dominant feature do not represent coherent oscillations like those of the principal feature.

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Figure 9:  $B_2$  against  $B_d$ , for  $O(10^3)$  clusters with various values of  $s_d$ , N,  $R_C$ , and other physical parameters (Appendix D) in the linear (a:  $A = 2 \times 10^{-2}$ ), transition (b: A = 1.2), and nonlinear (c: A = 20) regimes.

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