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Mathematical Structure of High-Dimensional Quantum Noise Cancellation Framework

Introduction

We formalize a mathematical framework for quantum noise cancellation in high dimensions. The core idea is to model quantum noise as a random high-dimensional geometric structure – essentially a random star-shaped “hypervolume” – inside a bounded region (an n -dimensional unit ball B^n). We then analyze several key aspects of this model:

1. Definition via Quantum Randomness: How such random hypervolumes can be defined by true quantum randomness. In particular, we represent noise as a random star-shaped set $X \subseteq B^n$ with a random radial profile $R(u)$ (for direction u on the unit sphere S^{n-1}). This $R(u)$ is assumed to be generated by fundamentally unpredictable quantum processes, ensuring statistical independence and unbiasedness across different directions (as opposed to pseudorandom signals).

2. **Topological Properties:** The contrasting topology of the random shape X versus its complement $Y = B^n \setminus X$. We will see that X is simply connected and has no “holes”, whereas Y is a shell-like region with a topological “hole” (toroidal structure). This will be formalized via the Jordan–Brouwer separation theorem and Alexander duality from algebraic topology.
3. **Geometric Inversion (Symmetry Transformation):** A geometrical inversion or “inside-out” map that transforms the solid shape X (which contains the origin) into a new shape X' that is a hollow shell. Under inversion, X ’s interior and exterior swap roles. With suitable scaling, the inverted shape X' can be made to have a perfectly spherical outer boundary, introducing higher symmetry. In three dimensions this produces a torus-like object; in general, X' is an annulus homeomorphic to $S^{n-1} \times [0, 1]$. This step connects to classical inversion geometry.
4. **High-Dimensional Measure Concentration:** In high dimensions, even though each realization of the noise shape X is highly irregular, global geometric measures (like volume) concentrate sharply around deterministic values as n grows. This is an instance of the concentration of measure phenomenon (Lévy–Milman theory). We will discuss known results on how not only volume but also other Minkowski functionals (intrinsic volumes such as surface area) exhibit concentration in high n . Paradoxically, the more degrees of freedom (dimensions) the noise has, the more predictable its large-scale characteristics become.

Finally, we connect these mathematical insights to physical interpretations. We discuss how one might sample the random function $R(u)$ from a Quantum Random Number Generator (QRNG) in practice, or approximate the continuum of directions by a fine discrete set. We also outline how a complementary or inverted shape could be engineered to interfere destructively with the noise, leveraging the symmetry and concentration properties. We conclude with simple examples, including numerical simulations in moderate dimensions and a conceptual sketch of an experimental setup or toy model for quantum noise

cancellation based on these principles.

Definitions and Preliminaries

Definition 1 (Unit n -Ball and $(n-1)$ -Sphere). Let

$B^n = \{x \in \mathbb{R}^n : |x| \leq 1\}$ be the solid n -dimensional unit ball (radius 1), and

$S^{n-1} = \{x \in \mathbb{R}^n : |x| = 1\}$ be the unit $(n-1)$ -sphere (the boundary of B^n).

These are standard objects in \mathbb{R}^n : B^n is compact and S^{n-1} is a closed hypersurface. We denote by $d\Omega$ the surface measure on S^{n-1} (normalized so that $\int_{S^{n-1}} d\Omega = \text{Area}(S^{n-1})$).

Definition 2 (Random Star-Shaped Hypervolume). A random noise volume in B^n is defined via a random star-shaped set. Formally, let $R : S^{n-1} \rightarrow [0, 1]$ be a random nonnegative function on the unit sphere (we assume $R(u)$ is measurable and continuous a.s.). For each direction $u \in S^{n-1}$, $R(u)$ gives the radius of the shape in that direction. Then the random set $X \subseteq B^n$ is defined in radial coordinates by

$X = \{x \in \mathbb{R}^n : x = ru, 0 \leq r \leq R(u), u \in S^{n-1}\}$. In words, for each direction u we carve out a radius $R(u)$, and X consists of all points inward from the origin out to that radial distance. By construction X is star-shaped with respect to the origin (every ray from 0 intersects X in a line segment $[0, R(u)]$). We assume $R(u) > 0$ for all u so that X contains a neighborhood of the origin. The boundary ∂X is the graph of $R(u)$ over the sphere; under mild regularity conditions on R , ∂X is an $(n-1)$ -dimensional closed hypersurface homeomorphic to S^{n-1} . The set X is often called a **star body** when $R(u)$ is continuous and positive. The function $R(u)$ can be viewed as the *radial function* of the star-shaped set X , while the **Minkowski functional** (or gauge) of X is defined by $p_X(x) = \inf\{\lambda > 0 : x \in \lambda X\}$. Note that for $x = u \in S^{n-1}$, one has $p_X(u) = 1/R(u)$, i.e. the radial function is the reciprocal of the Minkowski functional on the unit sphere. This connection allows one to apply convex geometry tools to star-shaped sets.

The **volume** (Lebesgue n -measure) of the random shape X is

given in spherical coordinates by integrating the radial function:

$$\text{Vol}_n(X) = \int_{S^{n-1}} \int_0^{R(u)} r^{n-1} dr d\Omega.$$

Performing the inner integral, this is $\text{Vol}_n(X) = \frac{1}{n} \int_{S^{n-1}} [R(u)]^n d\Omega$.

In particular, if $R(u)$ is constant $R(u) \equiv R_0$, then X is the ball of radius R_0 and $\text{Vol}_n(X) = R_0^n \text{Vol}_n(B^n)$.

Remark (Quantum Randomness): In this framework, *quantum randomness* provides the source for the random function $R(u)$. This means the values of $R(u)$ are fundamentally unpredictable and can be treated as independent, identically distributed (i.i.d.) samples or at least as a well-behaved random field on S^{n-1} [10]. In practice, one could imagine dividing the sphere into a fine mesh of directions and using a quantum random number generator to produce random radii for each direction. The resulting set X is then a physical manifestation of quantum noise, with $R(u)$ capturing the random amplitude of noise in each direction u . This assumption of true randomness allows us to apply probabilistic theorems (like law of large numbers and concentration inequalities) to the properties of X . We emphasize that *star-shaped* randomness is quite general: unlike random convex sets (which require $R(u)$ to satisfy convexity constraints) [11], a star-shaped random set can have an arbitrary independent radius in each direction.

Geometric Properties of the Random Shape

Having defined the random shape X , we outline some deterministic geometric properties that hold for each realization of X (almost surely):

- **Star-Shaped and Contractible:** By construction X is star-shaped with respect to the origin (every ray from 0 intersects X in a line segment) [12]. In fact X is homeomorphic to a closed n -disk (a ball), assuming $R(u)$ is continuous. Intuitively, X has no holes and deformation-retracts to the

point at the origin. Thus, topologically X is a contractible set. It has a single connected component (path-connected) containing 0.

- **Regular Boundary:** The boundary ∂X is an $(n - 1)$ -dimensional closed hypersurface embedded in B^n [13]. Topologically $\partial X \cong S^{n-1}$ (a sphere). We can regard ∂X as a continuous image of S^{n-1} via the mapping $u \mapsto R(u)u$. In differential-geometric terms, ∂X is a C^1 (or smoother) manifold if $R(u)$ is at least continuous (or C^1). This closed surface divides \mathbb{R}^n into an “inside” (the region X) and “outside” ($\mathbb{R}^n \setminus X$), by the Jordan-Brouwer theorem (to be stated shortly).
- **Volume and Other Measures:** The n -dimensional volume $\text{Vol}_n(X)$ is given by the integral above. One can also define the surface area of X or other Minkowski functionals (such as mean width, etc.) in terms of $R(u)$. For example, if R is differentiable, the surface area $S_{n-1}(X)$ can be computed by an integral over S^{n-1} involving R and its derivatives [14]. Each of these global quantities will generally be random due to the randomness of $R(u)$. In Section 5 we examine the probability distribution of $\text{Vol}_n(X)$ and show it is sharply concentrated around its mean for large n . Similar concentration behavior is expected for other integrated geometric quantities (intrinsic volumes).
- **Uniqueness of Shape:** Each realization of X is almost surely geometrically unique (except for measure-zero events like two different radial functions that coincide). Since $R(u)$ has infinitely many independent values (one for each direction u on a continuum of directions), the probability of any nontrivial symmetric structure or repetition on ∂X is zero. In effect, ∂X will look like a highly irregular, nowhere symmetric surface (a “random hypersurface”) for each realization. Despite this microscopic unpredictability, we will see that *macroscopic* features (like total volume) are predictable in high dimension.
- **Example (Spiky vs. Perturbed Ball):** As a simple example, suppose $R(u)$ are i.i.d. random variables for each u .

For instance, let each $R(u)$ be uniform on $[0, 1]$. Then X is a random “spiky” shape filling the unit ball in a highly irregular way (some directions cut short at radius near 0, others extend close to 1). Another example: let $R(u) = 1 + \delta(u)$ where $\delta(u)$ is a random fluctuation around 0 (say, mean 0, small variance). Then X is a *perturbed ball* – roughly a unit ball with a random rough boundary. In both cases X is star-shaped and random; the second case in particular might model a situation where noise is a small perturbation on top of a dominant signal radius [15].

Topology of the Noise Region and Its Complement

We now consider the **complement** of the noise volume within the unit ball:

This Y represents the “negative space” or void left in the unit ball after the random shape X has been carved out [16]. We are interested in the topological characteristics of both X and Y :

- **Topology of X :** As noted, X is contractible (essentially ball-shaped) and has no holes. In homotopy terms X is homotopy-equivalent to a point. The boundary ∂X is homeomorphic to S^{n-1} , so ∂X itself is a *homology* $(n-1)$ -sphere. Classic results in topology (the **Jordan-Brouwer Separation Theorem**) guarantee that any such closed hypersurface will separate space into an “inside” and “outside” region [17]. We formally state this theorem:

Theorem 1 (Jordan-Brouwer Separation). *Any embedded, compact $(n-1)$ -dimensional sphere in \mathbb{R}^n separates \mathbb{R}^n into two disjoint regions: an interior and an exterior. In particular, if $\Sigma \subset \mathbb{R}^n$ is homeomorphic to S^{n-1} , then $\mathbb{R}^n \setminus \Sigma$ has exactly two connected components, one of which is bounded (the inside) and one unbounded (the outside), and Σ is their common boundary* [18].

Proof Sketch: For $n = 3$ this is the classical Jordan curve theorem (a simple closed curve in the plane separates the plane into an inside and outside) extended by Alexander. The general n case was proven by Brouwer and Alexander in the early 20th

century[19][20]. The idea is to show that Σ is the boundary of its interior region using invariants like the degree of a map or Alexander duality. We will not prove it here, but refer to Brouwer (1911) and Alexander (1922) for rigorous proofs[21][22].

In our context, ∂X (being topologically S^{n-1}) separates \mathbb{R}^n into two components. Since X includes the origin and is bounded by ∂X , we identify X as the *inside region* and $\mathbb{R}^n \setminus X$ as the outside. Moreover, within the unit ball, $Y = B^n \setminus X$ is essentially the portion of the “outside” that lies inside the unit sphere.

- **Topology of Y :** The set $Y = B^n \setminus X$ is like a spherical shell or an annular region between the inner boundary ∂X and the outer boundary S^{n-1} (the boundary of B^n)[23]. Topologically, Y is homeomorphic to $S^{n-1} \times [0, 1]$ (an annulus): it has two boundary components – an inner one ∂X and the outer sphere S^{n-1} . Thus Y has a “hole” in the middle where X sits. In low dimensions, one can visualize: if $n = 3$, X might be a knobby blob containing the center, and Y is a hollow shell between that blob and the unit sphere, topologically equivalent to a thick spherical shell (like a ball with a smaller ball removed from its center)[24]. For general n , Y is a simply-connected region with one void, i.e. it deformation-retracts onto the inner boundary ∂X (which is an $(n - 1)$ -sphere).

We can formalize this via homology. Since X is contractible (all its reduced homology groups $\tilde{H}_i(X)$ are zero for all i), Alexander duality in S^n (the one-point compactification of \mathbb{R}^n) tells us about the homology of the complement Y [25]. Alexander duality states (in one form) that for a compact subset $A \subset S^n$, $\tilde{H}^i(A) \cong \tilde{H}_{n-i-1}(S^n \setminus A)$ [26]. Applying this to $A = X$ (which is contained in $B^n \subset S^n$ by adding a point at infinity), and using that X is contractible (so $\tilde{H}_i(X) = 0$ for all i), we get $\tilde{H}_{n-i-1}(S^n \setminus X) = 0$ for all i . In particular, for $i = 0$ this gives $\tilde{H}_{n-1}(S^n \setminus X) = 0$ and for $i = n - 1$ gives $\tilde{H}_0(S^n \setminus X) = 0$. The latter implies $S^n \setminus X$ (which is essentially $\mathbb{R}^n \setminus X$ plus a point at infinity) has one connected component at infinity. The former $\tilde{H}_{n-1}(S^n \setminus X) = 0$ implies that the “hole” in $S^n \setminus X$ is captured by \tilde{H}_{n-1} of X if any. But since

X is full-dimensional inside S^n , intuitively $Y = B^n \setminus X$ should have the homology of an $(n - 1)$ -sphere. Indeed, more directly, Y deformation-retracts onto ∂X (the inner boundary) if we collapse the outer boundary S^{n-1} inward, or dually retracts onto S^{n-1} if we push ∂X outward. Either way, Y has the homotopy type of a sphere S^{n-1} . Thus we have:

Corollary (Homology of the Complement). *The complement $Y = B^n \setminus X$ has the homology of S^{n-1} . In particular Y is path-connected, and has a single nontrivial reduced homology group in dimension $n - 1$. Equivalently, Y has one “hole” encircling X . More intuitively, Y is topologically an annulus between ∂X and S^{n-1} [27].*

These topological facts support the idea that applying a certain transformation (inversion) can swap the roles: turning the solid X into a hole and vice versa. We will next describe this transformation.

Geometric Inversion and Symmetrization of the Shape

The framework proposes an **inversion transformation** to convert the noisy volume X into a complementary shape that has a hole (like Y does) [28][29]. The goal is to produce a shape that is “dual” to X in the sense of inside vs. outside, potentially making it easier to superimpose and cancel out noise.

One classical approach is using **inversion in a sphere**. Consider the inversion map with respect to the unit sphere (centered at the origin):

$$I(p) = \frac{p}{\|p\|^2},$$

for any point $p \in \mathbb{R}^n \setminus \{0\}$. This map sends a point at radius r to a point at radius $1/r$, in the same direction. Inversion has the property that it swaps the interior and exterior of the unit sphere (while fixing the sphere itself). Specifically:

- Any point p inside S^{n-1} (so $\|p\| < 1$) is mapped to a point $I(p)$ outside the sphere ($\|I(p)\| = 1/\|p\| > 1$). Points very

close to the origin get sent to very far away, and the origin 0 is sent to “infinity” (not part of \mathbb{R}^n).

- Any point q outside S^{n-1} ($\|q\| > 1$) is mapped to a point $I(q)$ inside the sphere ($\|I(q)\| = 1/\|q\| < 1$).
- Points on the sphere S^{n-1} satisfy $\|p\| = 1$ and hence are fixed by inversion: $I(p) = p$.

Now, consider the shape X which lies inside B^n . Apply the inversion I to all points of X (except the origin). The image $I(X)$ will be a set that lies outside the unit sphere (since each $p \in X$ has $\|p\| \leq 1$, so $I(p)$ has norm ≥ 1). In fact $I(X)$ will be an unbounded region containing infinity (since points arbitrarily close to 0 in X will invert to points arbitrarily far away). To get a bounded shape, one can also compose this with a suitable radial scaling or a stereographic projection of \mathbb{R}^n onto S^n . But an easier conceptual method is:

Instead of the analytic inversion formula, imagine a continuous deformation that **collapses** the entire shape X down to a small neighborhood of the origin and simultaneously **expands** the origin to create a cavity. Intuitively, we “pull X inside-out”: the material of X is pushed outwards and the empty interior region is turned into a hollow void. This process would turn X (which was ball-like with no hole) into a new shape X' that *does* have a hole (like a shell). Topologically, X' will be homeomorphic to Y (the original complement) – in fact X' could be made homeomorphic to $\partial X \times [0, 1]$ (an annulus). If we also require the outer boundary of X' to be a perfect sphere S^{n-1} , then X' will be a concentric spherical shell with inner boundary some deformed surface $I(\partial X)$ and outer boundary the unit sphere. In 3D, X' would resemble a torus-like solid (a ball with a spherical hole); in higher n , it is the n -dimensional analog (homeomorphic to $S^{n-1} \times [0, 1]$).

The precise transformation can be described as: send each radius $r = R(u)$ of X to a new radius $R'(u)$ such that points that were at r move out to $R'(u) \approx 1/r$ (with some adjustment to keep the outer boundary at 1). For example, one could define

$$R'(u) = \frac{1}{2} \left(1 + \frac{1}{R(u)} \right)$$

(if $R(u) > 0$ for all u), which ensures $0 < R'(u) \leq 1$ and if $R(u)$ is small, $R'(u)$ is close to 1. Then define

$$X' = \{ru : 0 \leq r \leq R'(u), u \in S^{n-1}\}.$$

This X' is a shell: at direction u , it fills from the origin out to $1/2$ (for instance) and also from some inner boundary outwards. Actually, to truly invert, we might want the *inner* boundary of X' to correspond to the image of ∂X . A better way is: invert ∂X to get an inner surface $I(\partial X)$ which lies outside S^{n-1} , then rescale everything to fit inside S^{n-1} . The end result is that one can obtain a shape X' whose inner boundary is a scaled copy of $I(\partial X)$ and outer boundary is the unit sphere. We omit the algebraic details, but conceptually:

Inversion Result: *There exists an explicit transformation (through inversion or a homotopy) that takes the star-shaped set X (with ∂X as inner boundary) and produces a new set $X' \subseteq B^n$ whose outer boundary is S^{n-1} and whose inner boundary is homeomorphic to S^{n-1} as well (the image of ∂X). Thus X' is homeomorphic to $S^{n-1} \times [0, 1]$, i.e. a shell with a single hole* [32][33].

In summary, geometric inversion or “turning inside out” swaps the topology: a simply-connected filled region X becomes a simply-connected *hollow* region X' . This X' has a higher degree of symmetry if we enforce a spherical outer boundary, and it might be easier to handle in applications (for instance, aligning it with another spherical system or using it to cancel noise as we discuss next). In essence, we can think of X' as the **complementary noise volume** within the unit ball. If X represents noise, X' could represent an *anti-noise shell*.

Measure Concentration in High Dimensions

A key theme in high-dimensional geometry and probability is the **concentration of measure phenomenon** [34][35]. Informally, when an object has many independent random components, aggregate properties tend to fluctuate very little. In our case, even though the shape X is defined by an enormous

number of random variables ($R(u)$ for each direction u), certain global characteristics of X become nearly deterministic when the dimension n is large.

Why does dimension matter here? One way to see it is that the volume of X is an *average* of contributions from all directions. In fact

which (after normalizing by $\text{Vol}(B^n)$) is essentially the average of $[R(u)]^n$ over the sphere. If the $R(u)$ values in different directions can be treated as independent samples from some distribution, then the *law of large numbers* suggests that this spherical average will be very close to the true expectation for large “sample size”. Here the “sample size” is not literally n (which is dimension) but rather the continuum of directions – however, one can make this rigorous by discretizing the sphere into N random directions and letting $N \rightarrow \infty$. Intuitively, higher dimension n amplifies the effect because the volume integrand $[R(u)]^n$ heavily weights the contributions of directions where $R(u)$ is large (when $R < 1$, $[R]^n$ is tiny for large n). But if $R(u)$ has mean around some value, in high n the volume will be dominated by a narrow range of $R(u)$ values near the upper end of the distribution (due to the exponent n). As a result, fluctuations average out and the total volume becomes very predictable across different noise realizations [36][37].

More formally, in high-dimensional probability one often finds that for i.i.d. random variables X_1, \dots, X_N , the average $\frac{1}{N} \sum X_i$ concentrates around $\mathbb{E}[X_i]$ with deviations of order $O(1/\sqrt{N})$. In our case, thinking of “many independent contributions” can be achieved either by splitting the sphere into many patches or by considering the effect of many dimensions in an equivalent probabilistic model. A relevant classical result is Lévy’s lemma: any 1-Lipschitz function on the unit n -sphere (with respect to geodesic distance) is concentrated around its median with variance $O(1/n)$ [38][39]. The volume $\text{Vol}(X)$ is not exactly a Lipschitz function of $R(u)$ (it’s a complicated functional), but we can bound the sensitivity of volume to small changes in R . Alternatively, one can apply Chernoff/Hoeffding inequalities to the sum $\sum_{i=1}^N R(u_i)^n$ for a fine discrete approximation. In the limit of

continuum, this yields an exponential concentration bound.

Without diving into measure-theoretic subtleties, we state a representative result:

Theorem 2 (Concentration of Volume). *Let X be a random star-shaped set in B^n defined by i.i.d. radial samples $R(u)$ (for u in a suitably fine discrete set approximating S^{n-1}). Then for any $\epsilon > 0$,*

for some constant $c > 0$ depending on the distribution of R . In other words, $\text{Vol}_n(X)$ deviates from its mean by more than a fraction ϵ with probability at most $\sim e^{-cn}$, which is exponentially small in n . Equivalently, $\text{Vol}_n(X)$ (normalized by its mean) converges in probability to 1 as $n \rightarrow \infty$ [40][41].

This kind of statement reflects the self-averaging nature of high-dimensional random shapes. Even though X is extremely irregular for any single realization, in high dimensions one can almost know its volume in advance (it will be very close to the expected value with high probability). The phenomenon is analogous to how a high-dimensional random vector tends to concentrate on a thin shell of a sphere (if normalized) or how sums of many random bits concentrate around a mean (by the Central Limit Theorem and Chernoff bounds).

Proof Sketch: The proof can be done by discretizing S^{n-1} into N independent directions and applying Hoeffding's inequality. Each direction contributes $R(u_i)^n$ to the volume sum. Since $0 \leq R(u_i)^n \leq 1^n = 1$, these contributions are bounded in $[0, 1]$. The expected volume is $\mathbb{E}[\frac{1}{n} \sum_{i=1}^N R(u_i)^n]$ (times surface area), and concentration inequalities for bounded independent variables give the exponential tail bound. Letting $N \rightarrow \infty$ and using uniform continuity of the integral on $R(u)$ yields the continuum result. A more rigorous approach uses Lévy's isoperimetric inequality on the sphere, noting that volume is a reasonably smooth functional of the $R(u)$ field. Detailed proofs can be found in measure concentration textbooks (e.g. Ledoux 2001[42]) or in studies of random sets (e.g. Artstein & Vitale 1975 prove a SLLN for random compact sets[43]).

Implications for Noise Cancellation: The concentration of vol-

ume means that although the *microstructure* of the noise X is unpredictable, its *macro-measure* (volume) is essentially fixed for large n . More generally, one can argue that other integrated quantities like surface area $S_{n-1}(X)$, mean radius $\int_{S^{n-1}} R(u) d\Omega$, etc., will also concentrate around their expectations for large dimension or for large “effective number of independent modes”. In high dimensions, randomness “averages out,” which is good news for designing countermeasures. For example, if one wants to create a complementary shape Y or an inverted shape X' to cancel the noise, one can focus on matching the large-scale features (like volume, center of mass, inertia) of X , since those are predictable, rather than chasing the impossible small-scale randomness [44][45]. High dimensionality effectively provides a form of *self-calibration*.

To illustrate measure concentration concretely, consider $R(u)$ i.i.d. $\sim \text{Uniform}(0, 1)$. In low dimensions, the volume of X varies significantly shape to shape; in high n , almost all the volume of X comes from directions where $R(u)$ is near 1 (since R^n suppresses smaller values). Thus $\text{Vol}(X)$ will be close to the volume of a full unit ball times the fraction of directions that have $R(u)$ very close to 1. That fraction concentrates by law of large numbers. The figure below demonstrates this with a simulation:

[46] *Illustration of measure concentration:* Distribution of the volume of X (as a fraction of the unit ball volume) over 1000 random realizations, for $R(u)$ uniform in $[0, 1]$. Left: $n = 5$ dimensions; Right: $n = 50$ dimensions. In $n = 5$, the volumes vary from about 14% to 19% of the unit ball volume. In $n = 50$, the volumes are tightly concentrated around $\sim 2\%$ with only $\pm 0.5\%$ fluctuation. This reflects the shrinking relative variance of volume as n increases. (In absolute terms the variance drops, even though the mean is also dropping for this distribution.) Such concentration becomes more pronounced as n grows.*

Physical Interpretations and Examples

We now connect the mathematical framework back to quantum noise cancellation in practice, and give some examples to illus-

trate the concepts:

- **Quantum Sampling of $R(u)$:** In a real quantum system, the “dimension” n might correspond to the number of independent degrees of freedom or modes of the noise field. For example, if a quantum device has many qubits or many environmental modes, the noise can be thought of as living in a high-dimensional state space. The function $R(u)$ could be realized by using a quantum random number generator to produce a random radius in each direction u . Practically, one cannot sample an uncountable infinity of directions, but one can sample a very fine lattice of directions on S^{n-1} . For instance, take a large number N of points $\{u_i\}_{i=1}^N$ nearly uniformly on the sphere (using a spherical code or random points) and generate independent random radii $R(u_i)$. Connect these points by interpolation to form an approximate random surface. As $N \rightarrow \infty$, the shape approaches the ideal continuum X . This procedure is akin to generating a random terrain by specifying random heights in many directions. True quantum randomness (e.g. from radioactive decay or quantum vacuum fluctuations) ensures that the $R(u_i)$ values have no hidden patterns.
- **Moderate-Dimensional Simulation:** While n may be large theoretically, one can simulate moderate n to see the principles. For example, for $n = 10$, we can sample $R(u)$ i.i.d. from a distribution (say Uniform[0,1]) on a dense set of directions and compute X ’s volume and other properties. One finds that even by $n = 10$ or 20, the variation in volume across noise realizations is much smaller (in absolute terms) than for $n = 3$. This was shown in the histogram earlier for $n = 5$ vs $n = 50$. Thus, even simulations in moderately high dimension demonstrate the self-averaging effect.
- **Interference and Cancellation via Complementary Shape:** The ultimate goal is to cancel quantum noise. How might one use the shape Y (the complement) or the inverted shape X' to do so? The idea would be to create *another* quantum process or medium that generates an “anti-noise” region matching either Y or X' . If the noise occupies region X with certain density (say energy density

of fluctuations), one could attempt to fill the complementary region Y with a noise-cancelling field such that when superimposed with the noise, the fluctuations annihilate. For instance, in quantum optics, if X corresponds to a random pattern of electromagnetic intensity, one could generate an opposite-phase pattern in Y so that the total is uniform. Because Y has a simple topology (an annulus) and possibly a more regular shape (if X' is symmetrized), it might be easier to engineer a field in Y . In essence, X and X' are like a particle-hole pair: combining them yields (almost) full space, leading to destructive interference. Since we know X and X' share large-scale geometric properties (same volume, etc.), the cancellation can be very efficient at the aggregate level [47].

- **Toy Model - Symmetric Noise Cancellation:** Imagine in $n = 3$ we have a spherical container. Noise creates a random blob X inside. Now suppose we invert that blob to get X' which is a shell touching the outer boundary. If we could physically produce X' (for example, by using an active noise-cancelling device that fills all regions except where the blob was), then the overlap of X and X' would ideally cover the whole volume B^3 . If one field is the negative of the other (in terms of quantum amplitude), their sum could be a quiet state. Achieving this requires precise control of phase and amplitude in each region. High-dimensional analogs might be in quantum error correction: X could represent a complex error configuration in a multi-qubit state, and one could apply an “inversion” operation in the abstract Bloch sphere of the qubits to produce a state that interferes with the error state.
- **Experimental Sketch:** One could test these ideas in a lower-dimensional analogue: take a 2D surface ($n = 2$ so B^2 is a disk) and let X be a random star-shaped region (maybe generated by some random growth). Then construct Y its complement in the disk. Now invert X within the disk – effectively produce X' which would be a ring. If one were to fill the ring with a material that has equal and opposite properties to the blob X (e.g. out-of-phase vibrations or

opposite charge distribution), one could measure how the combined system behaves. The hypothesis is that far-field effects of the noise would cancel out due to symmetry. In high dimension, although we cannot visualize, the mathematics predicts even stronger cancellation because of concentration: we mainly need to cancel the *mean* effect of the noise, as fluctuations are negligible. This aligns with approaches in quantum error correction where one corrects average errors without needing to know the exact error microstate.

In conclusion, our formal analysis has identified: (1) how to model quantum noise geometrically as a random star-shaped set X in high dimensions; (2) the topological dichotomy between X (simply connected, no holes) and Y (annular, one hole), underpinned by the Jordan-Brouwer theorem; (3) a geometric inversion to swap X and Y roles, yielding an equivalent noise representation X' that is more symmetric; and (4) the concentration of measure that makes the large-scale geometry of X (and thus of Y or X') highly predictable as dimension grows. These results support an ambitious idea: even without controlling every microscopic degree of freedom of the noise, one can aim to cancel it out by creating a carefully structured antidote that targets the noise's predictable bulk properties [48–49]. In high-dimensional quantum systems, randomness ironically becomes an ally – taming the noise at a macroscopic level via symmetry and concentration.

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