ANALYZING RECONSTRUCTION ARTIFACTS FROM ARBITRARY INCOMPLETE X-RAY CT DATA

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Abstract. This article provides a mathematical analysis of singular (nonsmooth) artifacts added to reconstructions by filtered backprojection (FBP) type algorithms for X-ray CT with arbitrary incomplete data. We prove that these singular artifacts arise from points at the boundary of the data set. Our results show that, depending on the geometry of this boundary, two types of artifacts can arise: object-dependent and object-independent artifacts. Object-dependent artifacts are generated by singularities of the object being scanned and these artifacts can extend along lines. They generalize the streak artifacts observed in limited-angle tomography. Object-independent artifacts, on the other hand, are essentially independent of the object and take one of two forms: streaks on lines if the boundary of the data set is not smooth at a point and curved artifacts if the boundary is smooth locally. We prove that these streak and curve artifacts are the only singular artifacts that can occur for FBP in the continuous case. In addition to the geometric description of artifacts, the article provides characterizations of their strength in Sobolev scale in certain cases.

The results of this article apply to the well-known incomplete data problems, including limited-angle and region-of-interest tomography, as well as to unconventional X-ray CT imaging setups that arise in new practical applications. Reconstructions from simulated and real data are analyzed to illustrate our theorems, including the reconstruction that motivated this work—a synchrotron data set in which artifacts appear on lines that have no relation to the object.

1. Introduction

Over the past decades computed tomography (CT) has established itself as a standard imaging technique in many areas, including materials science and medical imaging. One collects X-ray measurements from many different directions (lines) that are distributed all around the object. Then one reconstructs a picture of the interior of the object using an appropriate mathematical algorithm. In classical tomographic imaging setups, this procedure works very well because the data can be collected all around the object, i.e., the data are complete, and standard reconstruction algorithms, such as filtered backprojection (FBP), provide accurate reconstructions [33, 42]. However, in many CT problems, some data are not available, and this leads to incomplete (or limited) data sets. The reasons for data incompleteness might be patient related (e.g., to decrease dose) or practical (e.g., when the scanner cannot image all of the object, as in digital breast tomosynthesis).

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Classical incomplete data problems have been studied from the beginning of tomography, including limited-angle tomography, where the data can be collected only from certain view-angles [24,30]; interior or region-of-interest (ROI) tomography, where the X-ray measurements are available only over lines intersecting a subregion of the object [12,25,50]; or exterior tomography, where measurements are available only over all lines outside a subregion [32,47].

In addition, new scanning methods generate novel data sets, such as the synchrotron experiment [5,6] in Section 7 that motivated this research. That reconstruction, in Figure 1, includes dramatic streaks that are independent of the object and were not described in the mathematical theory at that time but are explained by our main theorems. A thorough practical investigation of this particular problem was recently presented in [5].

Regardless of the type of data incompleteness, in most practical CT problems a variant of FBP is used on the incomplete data to produce reconstructions [42]. It is well-known that incomplete data reconstruction problems that do not incorporate a priori information (as is the case in all FBP type reconstructions) are severely ill-posed (e.g., [31] or [34, Section 6] for limited-angle CT). Consequently, certain image features cannot be reconstructed reliably [46] and, in general, artifacts, such as the limited-angle streaks in Figure 2 in Section 4 can occur. Therefore, reconstruction quality suffers considerably, and this complicates the proper interpretation of images.

We consider the continuous case, so we do not evaluate discretization errors. By artifacts, we mean nonsmooth image features (singularities), such as streaks, that are added to the reconstruction by the algorithm and are not part of the original object (see Definition 3.3).

1.1. Related research in the mathematical literature. Our work is based on microlocal analysis, a deep theory that describes how singularities are transformed by Fourier integral operators, such as the X-ray transform. Early articles using microlocal analysis in tomography include [40], which considers nonlinear artifacts in X-ray CT, [46], which characterizes visible and invisible singularities from X-ray CT data, [18], which provided a general microlocal framework for admissible
complexes, and [28] which considers general measures on lines in \( \mathbb{R}^2 \). Subsequently, artifacts were extensively studied in the context of limited-angle tomography, e.g., [24] and then [15]. The strength of added artifacts in limited-angle tomography was analyzed in [35]. Similar characterizations of artifacts in limited-angle type reconstructions have also been derived for the generalized Radon line and hyperplane transforms as well as for other Radon transforms (such as circular and spherical Radon transform), see [1,16,17,36,37].

Metal in objects can corrupt CT data and create dramatic streak artifacts [3]. This can be dealt with as an incomplete data problem by excluding data over lines through the metal. Recently, this problem has been mathematically modeled in a sophisticated way using microlocal analysis in [39,43,51]. A related problem is studied in [8,38,41], where the authors develop a streak reduction method for quantitative susceptibility mapping. Moreover, microlocal analysis has been used to analyze properties of related integral transforms in pure and applied settings [4,13,18,49,54].

1.2. Basic mathematical setup and our results. We use microlocal analysis to present a unified approach to analyze reconstruction artifacts for arbitrary incomplete X-ray CT data that are caused by the choice of data set. We not only consider all of the above mentioned classical incomplete data problems but also emerging imaging situations with incomplete data. We provide a geometric characterization of the artifacts and we prove it describes all singular artifacts that can occur for FBP type algorithms in the continuous case.

If \( f \) is the density of the object to be reconstructed, then each CT measurement is modeled by a line integral of \( f \) over a line in the data set. As we will describe in Section 2.1 we parametrize lines by \( (\theta, p) \in S^1 \times \mathbb{R} \), and the CT measurement of \( f \) over the line \( L(\theta, p) \) is denoted \( Rf(\theta, p) \). With complete data, where \( Rf(\theta, p) \) is given over all \( (\theta, p) \in S^1 \times \mathbb{R} \), accurate reconstructions can be produced by the FBP algorithm. In incomplete data CT problems, the data are taken over lines \( L(\theta, p) \) for \( (\theta, p) \) in a proper subset, \( A \), of \( S^1 \times \mathbb{R} \) and, even though FBP is designed for complete data, it is still one of the preferred reconstruction methods in practice, see [42]. As a result, incomplete data CT reconstructions usually suffer from artifacts.

We prove that incomplete data artifacts arise from points at the boundary or “edge” of the data set, \( \text{bd}(A) \), and we show that there are two types of artifacts: object-dependent and object-independent artifacts. The object-dependent artifacts are caused by singularities of the object being scanned. In this case, artifacts can appear along a line \( L(\theta_0, p_0) \) (i.e., a streak) if \( (\theta_0, p_0) \in \text{bd}(A) \) and if there is a singularity of the object on the line (such as a jump or object boundary tangent to the line)—this singularity of the object “generates” the artifact (see Theorem 3.7 A.). The streak artifacts observed in limited-angle tomography are special cases of this type of artifact.

The object-independent artifacts are essentially independent of the object being scanned (they depend primarily on the geometry of \( \text{bd}(A) \)) and they can appear either on lines or on curves. If the boundary of \( A \) is smooth near a point \( (\theta_0, p_0) \in \text{bd}(A) \), then we prove that artifacts can appear in the reconstruction along curves generated by \( \text{bd}(A) \) near \( (\theta_0, p_0) \), and they can occur whether the object being scanned has singularities or not (see Theorem 3.5 [B]). We also prove that, if \( \text{bd}(A) \) is not smooth (see Definition 3.2) at a point \( (\theta_0, p_0) \), then, essentially independently of the object, an artifact line can be generated all along \( L(\theta_0, p_0) \) (see Theorem 3.5 [C]).

We will illustrate our results with reconstructions for classical problems including limited-angle tomography and ROI tomography, as well as problems with novel data sets, including the synchrotron data set in Figure 1. In addition, we provide estimates of strength of the artifacts in Sobolev scale.

To the best of our knowledge, the mathematical literature up until now used microlocal and functional analysis to explain streak artifacts on lines that are generated by singularities of the object, and they exclusively focused on specific problems, primarily limited-angle tomography (e.g., [15,24,35]). Important work was done to analyze visible singularities for ROI (or local)
tomography (e.g., \[12, 25, 28, 46, 50\]). However, we are not aware of any reference where a microlocal explanation for the ring artifact in ROI CT was provided, although researchers are well aware of the ring itself (e.g., \[7, 10\]). We are also not aware of microlocal analyses of more general imaging setups, such as the nonstandard one presented in Figure 1.

1.3. Organization of the article. In Section 2, we provide notation and some of the basic ideas about wavefront sets. In Section 3 we give our main theoretical results, and in Section 4, we apply them to explain added artifacts in reconstructions from classical and novel limited data sets. In Section 5, we describe the strength of added artifacts in Sobolev scale. Then, in Section 6, we describe a simple, known method to decrease the added artifacts and provide a reconstruction and theorem to justify the method. We provide more details of the synchrotron experiment in Section 7 and observations and generalizations in Section 8. Finally, in the appendix, we give some technical theorems and then prove the main theorems.

2. Mathematical basis

Much of our theory can be made rigorous for distributions of compact support (see \[14, 52\] for an overview of distributions), but we will consider only Lebesgue measurable functions. This setup is realistic in practice, and our theorems are simpler in this case than for general distributions. Remark A.4 provides perspective on this.

The set $L^2(D)$ is the set of square-integrable functions on the closed unit disk $D = \{ x \in \mathbb{R}^2 : ||x|| \leq 1 \}$. The set $L^2_{loc}(\mathbb{R}^2)$ is the set of locally square-integrable functions—functions that are square-integrable over every compact subset of $\mathbb{R}^2$. We define $L^2_{loc}(S^1 \times \mathbb{R})$ in a similar way where $S^1$ is the circle of unit vectors in $\mathbb{R}^2$.

2.1. Notation. Let $(\theta, p) \in S^1 \times \mathbb{R}$, then the line perpendicular to $\theta$ and containing $p\theta$ is denoted

\[
L(\theta, p) = \{ x \in \mathbb{R}^2 : x \cdot \theta = p \}.
\]

Note that $L(\theta, p) = L(-\theta, -p)$. For $\theta \in S^1$ let $\theta^\perp$ be the unit vector $\pi/2$ radians counterclockwise from $\theta$. We define the X-ray transform or Radon line transform of $f \in L^2(D)$ to be the integral of $f$ over $L(\theta, p)$:

\[
Rf(\theta, p) = \int_{-\infty}^{\infty} f(p\theta + t\theta^\perp) \, dt.
\]

The symmetry of our parametrization of lines gives the symmetry condition

\[
Rf(\theta, p) = Rf(-\theta, -p).
\]

For functions $g$ on $S^1 \times \mathbb{R}$, the dual Radon transform or backprojection operator is defined

\[
R^*g(x) = \int_{S^1} g(\theta, x \cdot \theta) \, d\theta.
\]

When visualizing functions on $S^1 \times \mathbb{R}$, we will use the natural identification

\[
\mathbb{R}^2 \ni (\varphi, p) \mapsto (\vartheta(\varphi), p) \in S^1 \times \mathbb{R} \quad \text{where} \quad \vartheta(\varphi) := (\cos(\varphi), \sin(\varphi)) \in S^1
\]

and for functions $g$ on $S^1 \times \mathbb{R}$ the identification

\[
\tilde{g}(\varphi, p) = g(\vartheta(\varphi), p) \quad \text{for} \quad (\varphi, p) \in \mathbb{R}^2.
\]

The sinogram of a function $g(\theta, p)$ is a grayscale picture on $[0, \pi] \times \mathbb{R}$ or $[0, 2\pi] \times \mathbb{R}$ of the mapping $(\varphi, p) \mapsto \tilde{g}(\varphi, p)$. 
2.2. Wavefront sets. In this section, we define some important concepts needed to describe singularities in general. Sources, such as [14], provide introductions to microlocal analysis. Generally cotangent spaces are used to describe microlocal ideas, but they would complicate this exposition, so we will identify a covector \((x, \xi dx)\) with the associated ordered pair of vectors \((x, \xi)\). The book chapter [26] provides some basic microlocal ideas and a more elementary exposition adapted for tomography.

The concept of the wavefront set is a central notion of microlocal analysis. It defines singularities of functions in a way that simultaneously provides information about their location and direction. We will employ this concept to define (singular) artifacts precisely, and we will use the powerful theory of microlocal analysis to analyze artifacts generated in incomplete data reconstructions in tomography.

In what follows, by a cutoff function at \(x_0 \in \mathbb{R}^2\), we will denote a \(C^\infty\)-function of compact support that is nonzero at \(x_0\). We now define singularities and the wavefront set.

**Definition 2.1 (Wavefront set [14, 55]).** Let \(x_0 \in \mathbb{R}^2\), \(\xi_0 \in \mathbb{R}^2 \setminus \mathbf{0}\), and \(f \in L^2_{\text{loc}}(\mathbb{R}^2)\). We say \(f\) is smooth at \(x_0\) in direction \(\xi_0\) if there is a cutoff function \(\psi\) at \(x_0\) and an open cone \(V\) containing \(\xi_0\) such that the Fourier transform \(\mathcal{F}(\psi f)(\xi)\) is rapidly decaying at infinity for \(\xi \in V\).

We say \(f\) has a singularity at \(x_0\) in direction \(\xi_0\), or a singularity at \((x_0, \xi_0)\), if \(f\) is not smooth at \(x_0\) in direction \(\xi_0\).

The wavefront set of \(f\), \(WF(f)\), is defined as the set of all singularities \((x_0, \xi_0)\) of \(f\).

\(f\) has a singularity at \(x_0\) if \(f\) is not smooth at \(x_0\) in some direction.

For \((x_0, \xi_0) \in WF(f)\), the first entry \(x_0\) will be called the base point of \((x_0, \xi_0)\). Hence, the base point of a singularity gives the location where the function \(f\) is singular (not smooth) in some direction. If we say \(f\) has a singularity at \(x_0\), we mean \(x_0\) is the base point of an element of \(WF(f)\).

As an example, let \(B\) be a subset of the plane with a smooth boundary and let \(f\) be equal to 1 on \(B\) and 0 off of \(B\). Then, \(WF(f)\) is the set of all points \((x, \xi)\) where the base points \(x\) are on the boundary of \(B\) and \(\xi\) is normal to the boundary of \(B\) at \(x\). In this case, \(f\) has singularities at all points of \(\text{bd}(B)\).

**Remark 2.2 (Wavefront set for functions defined on \(S^1 \times \mathbb{R}\)).** The notion of a singularity and the wavefront set can also be defined for functions \(g \in L^2_{\text{loc}}(S^1 \times \mathbb{R})\) using the identification (2.6).

In order to define \(WF(g)\), let \(\tilde{g}\) denote the locally square-integrable function on \(\mathbb{R}^2\) defined by (2.6). Let \((\theta, p) \in S^1 \times \mathbb{R}\) and \(\varphi \in \mathbb{R}\) with \(\theta = \theta(\varphi)\). Let \(\eta \in \mathbb{R}^2 \setminus \mathbf{0}\). Then, we say that \(g\) has a singularity at \(((\theta, p), \eta)\) if \(\tilde{g}\) has a singularity at \(((\varphi, p), \eta)\), i.e., \(((\varphi, p), \eta) \in WF(g)\) if \(((\varphi, p), \eta) \in WF(\tilde{g})\). In that case, the base point of a singularity of \(g\) is of the form \((\theta, p)\).

Note that the wavefront set is well-defined for functions on \(S^1 \times \mathbb{R}\) as both \(\tilde{g}\) and \(\varphi \mapsto \theta(\varphi)\) are \(2\pi\)-periodic in \(\varphi\).

**Definition 2.3.** Let \((\theta, p) \in S^1 \times \mathbb{R}\). The normal space of the line \(L(\theta, p)\) is
\[
(2.7)\quad N(L(\theta, p)) = \{(x, \omega \theta) : x \in L(\theta, p), \omega \in \mathbb{R}\}.
\]
For \(f \in L^2_{\text{loc}}(\mathbb{R}^2)\), the set of singularities of \(f\) normal to \(L(\theta, p)\) is
\[
(2.8)\quad WF_{L(\theta, p)}(f) = WF(f) \cap N(L(\theta, p)).
\]
If \(WF_{L(\theta, p)}(f) \neq \emptyset\), then we say \(f\) has a singularity (or singularities) normal to \(L(\theta, p)\).

If \(WF_{L(\theta, p)}(f) = \emptyset\), then we say \(f\) is smooth normal to the line \(L(\theta, p)\).

For \(x_0 \in \mathbb{R}^2\), we let
\[
WF_{x_0}(f) = WF(f) \cap \{(x_0) \times \mathbb{R}^2\}.
\]

\[\text{That is, for every } k \in \mathbb{N}, \text{ there is a constant } C_k > 0 \text{ such that } |\mathcal{F}(\psi f)(\xi)| \leq C_k/(1 + ||\xi||)^k \text{ for all } \xi \in V.\]
For \( g \in L^2_{\text{loc}}(S^1 \times \mathbb{R}) \), we define
\[
WF(\theta,p)(g) = WF(g) \cap (\{(\theta,p)\} \times \mathbb{R}^2).
\]

It is important to understand each set introduced in Definition \ref{def:wavefront}. In this case, the incomplete data are often extended by the algorithm to a precise concept of singularity.

The set \( WF_{x_0}(f) \) is the wavefront set of \( f \) above \( x_0 \), and \( WF_{x_0}(f) = \emptyset \) if and only if \( f \) is smooth in some neighborhood of \( x_0 \).

If \( g \in L^2_{\text{loc}}(S^1 \times \mathbb{R}) \), then \( WF(\theta,p)(g) \) is the set of wavefront directions with base point \((\theta,p)\). We will exploit the sets introduced in these definitions starting in the next section.

### 3. Main results

In contrast to limited-angle characterizations in \cite[15,24], our main results describe artifacts in arbitrary incomplete data reconstructions that include the classical limited data problems as special cases. Our results are formulated in terms of the wavefront set (Definition \ref{def:wavefront}), which provides a precise concept of singularity.

In many applications, reconstructions from incomplete CT data are calculated by the filtered backprojection algorithm (FBP), which is designed for complete data (see \cite{32} for a practical discussion of FBP). In this case, the incomplete data are often extended by the algorithm to a complete data set on \( S^1 \times \mathbb{R} \) by setting it to zero off of the set \( A \) (cutoff region) over which data are taken. Therefore, the incomplete CT data can be modeled as
\[
R_A f(\theta, p) = I_A(\theta, p)Rf(\theta, p),
\]
where \( I_A \) is the characteristic function of \( A \). Thus, using the FBP algorithm to calculate a reconstruction from such data gives rise to the reconstruction operator:
\[
L_A f = R^* (\Lambda R_A f) = R^* (\Lambda I_A Rf),
\]
where \( \Lambda \) is the standard FBP filter (see e.g., \cite[Theorem 2.5]{33} and \cite[§5.1.1]{34} for numerical implementations) and \( R^* \) is defined by \ref{eq:trans}.

Our next assumption collects the conditions we will impose on the cutoff region \( A \). There, we will use the notation \( \text{int}(A) \), \( \text{bd}(A) \), and \( \text{ext}(A) \) to denote the interior of \( A \), the boundary of \( A \), and the exterior of \( A \), respectively.

**Assumption 3.1.** Let \( A \) be a proper subset of \( S^1 \times \mathbb{R} \) (i.e., \( A \neq S^1 \times \mathbb{R} \)) with a nontrivial interior and assume \( A \) is symmetric in the following sense:
\[
\text{if } (\theta, p) \in A \text{ then } (-\theta, -p) \in A.
\]
In addition, assume that \( A \) is the smallest closed set containing \( \text{int}(A) \), i.e. \( A = \text{cl}(\text{int}(A)) \).

We now explain the importance of this assumption. Since \( A \) is proper, data over \( A \) are incomplete. Being symmetric means that, if \( (\theta, p) \in A \) then the other parameterization of \( L(\theta, p) \) is also in \( A \). We exclude degenerate cases, such as when \( A \) includes an isolated curve by assuming that
\[
A = \text{cl}(\text{int}(A)).
\]

Our next definition gives us the language to describe the geometry of \( \text{bd}(A) \).

**Definition 3.2** (Smoothness of \( \text{bd}(A) \)). Let \( A \subset S^1 \times \mathbb{R} \) and let \((\theta_0, p_0) \in \text{bd}(A)\).

- We say that \( \text{bd}(A) \) is smooth near \((\theta_0, p_0)\) if, for some neighborhood, \( U \) of \((\theta_0, p_0)\) in \( S^1 \times \mathbb{R} \), the part of \( \text{bd}(A) \) in \( U \) is a \( C^\infty \) curve. In this case, there is a unique tangent line in \((\theta, p)\)-space to \( \text{bd}(A) \) at \((\theta_0, p_0)\).
- If this tangent line is vertical (i.e., of the form $\theta = \theta_0$), then we say the boundary is vertical or has infinite slope at $(\theta_0, p_0)$.
- If this tangent line is not vertical, then $\text{bd}(A)$ is defined near $(\theta_0, p_0)$ by a smooth function $p = p(\theta)$. In this case, the slope of the boundary at $(\theta_0, p_0)$ will be the slope of this tangent line:

$$p'(\theta_0) := \frac{dp}{d\varphi}(\varphi(\varphi_0)) \quad \text{where} \; \varphi_0 \text{ is defined by } \varphi(\varphi_0) = \theta_0^3$$

- We say that $\text{bd}(A)$ is not smooth at $(\theta_0, p_0)$ if it is not a smooth curve in any neighborhood of $(\theta_0, p_0)$.
- We say that $\text{bd}(A)$ has a corner at $(\theta_0, p_0)$ if the curve $\text{bd}(A)$ is continuous at $(\theta_0, p_0)$, is smooth at all other points sufficiently close to $(\theta_0, p_0)$, and has one-sided tangent lines at $(\theta_0, p_0)$ but they are different lines.

3.1. **Singularities and artifacts.** In this section we define artifacts and visible and invisible singularities, and we explain why artifacts appear on lines $L(\theta, p)$ only when $(\theta, p) \in \text{bd}(A)$.

**Definition 3.3** (Artifacts and visible singularities). Every singularity $(x, \xi) \in \text{WF}(\mathcal{L}_A f)$ that is not a singularity of $f$ is called an artifact (i.e., any singularity in $\text{WF}(\mathcal{L}_A f) \setminus \text{WF}(f)$).

An artifact curve is a collection of base points of artifacts that form a curve.

A streak artifact is an artifact curve in which the curve is a subset of a line.

Every singularity of $f$ that is also in $\text{WF}(\mathcal{L}_A f)$ is said to be visible (from data on $A$), i.e., any singularity in $\text{WF}(\mathcal{L}_A f) \cap \text{WF}(f)$. Other singularities of $f$ are called invisible (from data on $A$).

Our next theorem gives an analysis of singularities in $\mathcal{L}_A f$ corresponding to lines $L(\theta, p)$ for $(\theta, p) \notin \text{bd}(A)$. It shows that the only singularities of $\mathcal{L}_A f$ that are normal to lines $L(\theta, p)$ for $(\theta, p) \in \text{int}(A)$ are visible singularities of $f$, and there are no singularities of $\mathcal{L}_A f$ normal to lines $L(\theta, p)$ for $(\theta, p) \in \text{ext}(A)$.

**Theorem 3.4** (Visible and invisible singularities in the reconstruction). Let $f \in L^2(D)$ and let $A \subset S^1 \times \mathbb{R}$ satisfy Assumption 3.1

A. If $(\theta, p) \in \text{int}(A)$ then $\text{WF}_{L(\theta, p)}(f) = \text{WF}_{L(\theta, p)}(\mathcal{L}_A f)$. Therefore, all singularities of $f$ normal to $L(\theta, p)$ are visible singularities, and $\mathcal{L}_A f$ has no artifacts normal to $L(\theta, p)$.

B. If $(\theta, p) \notin (A \cap \text{supp}(Rf))$, then $\text{WF}_{L(\theta, p)}(\mathcal{L}_A f) = \emptyset$. Therefore, all singularities of $f$ normal to $L(\theta, p)$ are invisible from data on $A$, and $\mathcal{L}_A f$ has no artifacts normal to $L(\theta, p)$.

C. If $x \in D$ and all lines through $x$ are parameterized by points in $\text{int}(A)$ (i.e., $\forall \theta \in S^1, (\theta, x \cdot \theta) \in \text{int}(A)$), then

$$\text{WF}_x(f) = \text{WF}_x(\mathcal{L}_A f).$$

In this case, all singularities of $f$ at $x$ are visible in $\mathcal{L}_A f$.

Therefore, artifacts occur only normal to lines $L(\theta, p)$ for $(\theta, p) \in \text{bd}(A)$.

This theorem follows directly from [46, Theorem 3.1] and continuity of $R^*$ (see also [28]). Note that Theorem 3.4C follows from parts A. and B. and is included because we will need it later.

3. Note that the map $\varphi \mapsto \varphi(\varphi)$ gives the local coordinates on $S^1$ near $\varphi_0$ and $\theta_0$ that are used in our proofs, and $p'$ is just the derivative of $p$ in these coordinates.

4. Precisely, there is an open neighborhood $U$ of $(\theta_0, p_0)$, an open interval $I = (a, b)$, two smooth functions $c_i : I \to U$, $i = 1, 2$, and some $t_0 \in I$ such that $c_1(t_0) = (\theta_0, p_0)$, $i = 1, 2$; the curves $c_1(I)$ and $c_2(I)$ intersect transversally at $(\theta_0, p_0)$; and $\text{bd}(A) \cap U = c_1((a, t_0)) \cup c_2((a, t_0))$.

5. Invisible singularities of $f$ are smoothed by $\mathcal{L}_A$ and reconstruction of those singularities is in general extremely ill-posed in Sobolev scale since any inverse operator must take each smoothed singularity back to the original non-smooth singularity, so inversion would be discontinuous in any range of Sobolev norms.
3.2. Analyzing singular artifacts. We now analyze artifacts in limited data FBP reconstructions using $L_A$ (3.2). In particular, we show that the nature of artifacts depends on the smoothness and geometry of $\text{bd}(A)$ and, in some cases, singularities of the object $f$.

Theorem 3.3 establishes that artifacts occur only above points on lines $L(\theta, p)$ for $(\theta, p) \in \text{bd}(A)$. Our next two theorems show that the only artifacts that occur are either artifacts on specific types of curves (see (3.6)) or streak artifacts, and they are of two types.

Let $f \in L^2(D)$ and let $(\theta, p) \in \text{bd}(A)$:

- **Object-independent artifacts**: those are caused essentially by the geometry of $\text{bd}(A)$.
  They can occur whether $f$ has singularities normal to $L(\theta, p)$ or not, and they can be curves or streak artifacts.

- **Object-dependent artifacts**: those are caused essentially by singularities of the object $f$ that are normal to $L(\theta, p)$. They will not occur if $f$ is smooth normal to $L(\theta, p)$ and they are always streak artifacts.

Our next theorem gives conditions under which artifact curves that are not streaks (i.e., not subsets of lines) appear in reconstructions from $L_A$.

**Theorem 3.5 (Artifact Curves).** Let $f \in L^2(D)$ and let $A \subset S^1 \times \mathbb{R}$ satisfy Assumption 3.1. Let $(\theta_0, p_0) \in \text{bd}(A)$ and assume that $\text{bd}(A)$ is smooth near $(\theta_0, p_0)$. Assume $\text{bd}(A)$ has finite slope at $(\theta_0, p_0)$ and let $I$ be a neighborhood of $\theta_0$ in $S^1$ such that $\text{bd}(A)$ is given by a smooth curve $p = p(\theta)$ near $(\theta_0, p_0)$. Let

$$x_b = x_b(\theta) = p(\theta)\theta + p'(\theta)\theta^\perp \in \mathbb{R}^2 \text{ for } \theta \in I.$$  

Then, an object-independent artifact curve can appear in $L_A f$ on the curve given by $I \ni \theta \mapsto x_b(\theta)$, which we will call the $x_b$-curve.

A. The $x_b$-curve is curved (i.e., not a subset of a line) unless it is a point.

B. Assume $f$ is smooth normal to $L(\theta_0, p_0)$.

1. Then,

$$WF_{L(\theta_0, p_0)}(L_A f) \subset \{(x_b(\theta_0), \omega \theta_0) : \omega \neq 0\}.$$  

2. If $Rf = 0$ in a neighborhood of $(\theta_0, p_0)$, then $WF_{L(\theta_0, p_0)}(L_A f) = \emptyset$ and this $x_b$-curve will not appear in the reconstruction $L_A f$ near $x_b(\theta_0)$.

3. If $Rf(\theta_0, p_0) \neq 0$, then equality holds in (3.7) and the $x_b$-curve will appear in the reconstruction $L_A f$ near $x_b(\theta_0)$.

Theorem 3.5 is proven in Appendix A.2. Figures 3, 4 and 5 in Section 4 all show $x_b$-artifact curves. The following remark discusses these curves in more detail.

**Remark 3.6.** Assume $\text{bd}(A)$ is smooth with finite slope at $(\theta_0, p_0)$. Let $I$ be a neighborhood of $\theta_0$ and let $p : I \to \mathbb{R}$ be a parametrization of $\text{bd}(A)$ near $(\theta_0, p_0)$. Note that

$$x_b(\theta) \in L(\theta, p) \text{ for } \theta \in I.$$  

If the slope of $\text{bd}(A)$ at $(\theta_0, p_0)$ is small enough, i.e.,

$$|p'(\theta_0)| < \sqrt{1 - p_0^2}$$  

holds, then the $x_b$-curve of artifacts $\theta \mapsto x_b(\theta)$ will be inside the closed unit disk, $D$, at least for $\theta$ near $\theta_0$. If not, then $x_b(\theta_0) \notin \text{int}(D)$. This is illustrated in Section 4 in Figure 3(A) for large slope--where (3.8) is not satisfied, and (3)(B) for small slope--where (3.8) is satisfied.

If $\text{bd}(A)$ is smooth and vertical at $(\theta_0, p_0)$ (infinite slope), then there will be no object-independent artifact on the line $L(\theta_0, p_0)$. This follows from the proof of this theorem because the singularity in the data that causes the $x_b$ curve is smoothed by $R^*$ in this case. Intuitively, if $\text{bd}(A)$ is vertical
then \( p'(\theta_0) \) is infinite and from [3.6], the point \( x_b(\theta_0) \) would be “at infinity.” In this case, only object-dependent streak artifacts can be generated by \((\theta_0, p_0)\), see Theorem 3.7 and Figures 2 and 3 in Section 4.

Our next theorem gives the conditions under which there can be streak artifacts in reconstructions using \( \mathcal{L}_A \).

**Theorem 3.7 (Streak artifacts).** Let \( f \in L^2(D) \) and let \( A \subset S^1 \times \mathbb{R} \) satisfy Assumption 3.1.

A. If \( f \) has a singularity normal to \( L(\theta_0, p_0) \), then a streak artifact can occur on \( L(\theta_0, p_0) \).

B. If \( f \) is smooth normal to \( L(\theta_0, p_0) \) and \( \text{bd}(A) \) is smooth and vertical at \((\theta_0, p_0)\), then \( \mathcal{L}_A f \) is smooth normal to \( L(\theta_0, p_0) \).

C. Let \((\theta_0, p_0) \in \text{bd}(A) \) and assume that \( \text{bd}(A) \) is not smooth at \((\theta_0, p_0)\). Then, \( \mathcal{L}_A f \) can have a streak artifact on \( L(\theta_0, p_0) \) independent of \( f \).

If \( f \) is smooth normal to \( L(\theta_0, p_0) \), then \( Rf(\theta_0, p_0) \neq 0 \), and \( \text{bd}(A) \) has a corner at \((\theta_0, p_0)\) (see Definition 3.4), then \( \mathcal{L}_A f \) does have a streak artifact on \( L(\theta_0, p_0) \), i.e.,

\[
\text{WF}_{L(\theta_0, p_0)}(\mathcal{L}_A f) = N(L(\theta_0, p_0)).
\]

The proof Theorem 3.7 is provided in Appendix A.2.

Part A. of Theorem 3.7 provides a generalization of classical limited-angle streak artifacts observed in Figure 2 in Section 4. Such limited-angle type artifacts can also be seen in Figures 3 and 5 in that section.

Part B. of Theorem 3.7 shows that the streak artifacts in Part A. are object-dependent.

Part C. of Theorem 3.7 explains the object-independent streak artifacts in Figure 5 that are highlighted in yellow as well as the object-independent streak artifacts that are observed in the real data reconstructions in Figures 6(A) and 9(A) in Section 7. In Theorem 5.2, we will describe the strength of the artifacts in Sobolev scale in specific cases of Theorems 3.5 and 3.7.

**Example 3.8.** Theorem 3.5 and Theorem 3.7 give necessary conditions under which \( \mathcal{L}_A f \) can have artifacts. We now provide an example when the conditions of those theorems hold for \( f \) and \( A \) but \( \mathcal{L}_A f \) has no artifacts. This is why we state in parts of Theorems 3.5 and 3.7 that artifacts can occur, rather than that they will occur.

Let \( A = \{(\theta, p) \in S^1 \times \mathbb{R} : |p| \leq 1\} \), then \( A \) represents the set of lines meeting the closed unit disk, \( D \). Let \( f \) be the characteristic function of \( D \). Then, for all \( x \in \text{bd}(D) = S^1 \), \( \xi = (x, x) \in \text{WF}(f) \), \( \xi \) is normal to the line \( L(x, 1) \), and \((x, 1)\), which is in \( S^1 \times \mathbb{R} \), is also in \( \text{bd}(A) \). Under these conditions, there could be a streak artifact on \( L(x, 1) \) by Theorem 3.7 A. Because \( \text{bd}(A) \) is smooth and not vertical, there could be an \( x_b \)-curve artifact by Theorem 3.5. However, \( 1_A Rf = Rf \) so \( \mathcal{L}_A f = f \) and there are no artifacts in this reconstruction.

Object-dependent streak artifacts were analyzed for limited-angle tomography in articles such as [15, 21, 35], but we are unaware of a reference to Theorem 3.7 A for general incomplete data problems. We are not aware of a previous reference in the literature to a microlocal analysis of the \( x_b \)-curve artifact as in Theorem 3.5 or to the corner artifacts as in Theorem 3.7 C. We now assert that all singular artifacts are classified by Theorems 3.5 and 3.7.

**Theorem 3.9.** Let \( f \in L^2(D) \) and let \( A \subset S^1 \times \mathbb{R} \) satisfy Assumption 3.1. The only singular artifacts in \( \mathcal{L}_A f \) occur on \( x_b \)-curves as described by Theorem 3.5 or are streak artifacts as described by Theorem 3.7.

Theorem 3.9 is proven in Section A.2.

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\(^6\)Note that Theorem 3.5 C states that, if \( f \) is smooth normal to \( L(\theta_0, p_0) \) and \( \text{bd}(A) \) is smooth and not vertical at \((\theta_0, p_0)\), then \( \mathcal{L}_A f \) is smooth normal to \( L(\theta_0, p_0) \) except possibly at \( x_b(\theta_0) \) (see (3.7)).
4. Numerical illustrations of our theoretical results

We now consider a range of well-known incomplete data problems as well as unconventional ones to show how the theoretical results in Section 3 are reflected in practice. All sinograms represent the data \( g(\theta, p) = Rf(\theta, p) \) using (2.6) and displaying them in the \((\varphi, p)\)-plane rather than showing them on \( S^1 \times \mathbb{R} \). To this end, we define

\[
\tilde{L}(\varphi, p) := L(\partial(\varphi), p),
\]

(4.1) \((\varphi, p) \mapsto \tilde{g}(\varphi, p) = g(\partial(\varphi), p)\) for \( \varphi \in [0, 2\pi] \), \( p \in [-\sqrt{2}, \sqrt{2}] \),

if \( A \subset S^1 \times \mathbb{R} \), then \( \tilde{A} := \{(\varphi, p) \in [0, 2\pi] \times \mathbb{R} : (\partial(\varphi), p) \in A\} \).

In this section, we will specify limited data using the sets \( \tilde{A} \subset [0, 2\pi] \times \mathbb{R} \) rather than \( A \subset S^1 \times \mathbb{R} \), and we will let \( R \) denote the Radon transform with this parametrization. Furthermore, because of the symmetry condition (2.3), we will display only the part of the sinogram in \([0, \pi] \times [-\sqrt{2}, \sqrt{2}]\). Except for the center picture in Figure 3(A) reconstructions are displayed on \([-1, 1]^2\).

4.1. Limited-angle tomography. First, we analyze limited-angle tomography, a classical problem in which Theorem 3.7 A. applies. In this case \( \text{bd}(\tilde{A}) \) consists of four vertical lines \( \varphi = \varphi_1, \varphi = \varphi_2, \varphi = \varphi_1 + \pi, \varphi = \varphi_2 + \pi \) for two angles \( 0 \leq \varphi_1 < \varphi_2 < \pi \) representing the ends of the angular range. Taking a closer look at the statement of Theorem 3.7 A. and the results of [15, 17] one can observe that, locally, they describe the same phenomena, namely: whenever there is a line \( \tilde{L}(\varphi_0, p_0) \) in the data set with \((\varphi_0, p_0) \in \text{bd}(\tilde{A})\) and which is normal to a singularity of \( f \), then a streak artifact can be generated on \( \tilde{L}(\varphi_0, p_0) \) in the reconstruction \( L_{\text{A}} f \). Therefore, Theorem 3.7 A. generalizes the results of [15] as it also applies to cutoff regions with non-vertical tangent.

It is important to note that, with limited-angle data, there are no object-independent artifacts since \( \text{bd}(\tilde{A}) \) is smooth and vertical (the \( x_b \)-curve is not defined).

Figure 2. Left: Limited-angle data (bd(\( \tilde{A} \)) is vertical). Center: FBP reconstruction. Right: Reconstruction highlighting object-dependent artifact lines tangent to skull corresponding to the four circled points in the sinogram.

Figure 2 illustrates limited-angle tomography. The boundary, \( \text{bd}(\tilde{A}) \), consists of the vertical lines \( \varphi = 4\pi/9 \) and \( \varphi = 5\pi/9 \). The artifact lines are exactly the lines with \( \varphi = 4\pi/9 \) or \( 5\pi/9 \) that are tangent to boundaries in the object (i.e., wavefront directions are normal to the line). The four circled points on the sinogram correspond to the object-dependent artifact lines at the boundary of the skull. The corresponding lines are tangent to the skull and have angles \( \varphi = 4\pi/9 \) and \( \varphi = 5\pi/9 \). One can also observe artifact lines tangent to the inside of the skull with these same angles.
One can notice invisible singularities of $f$—the top and bottom boundaries of the skull—at the top and bottom of the reconstruction. If the excluded region were larger, they would be more noticeable.

4.2. Smooth boundary with finite slope. We now consider the general case in Theorem 3.5 by analyzing the artifacts for a specific set $\tilde{A}$ which is defined as follows. It will be cut in the middle so that the left-most boundary of $A$ occurs at $\varphi = a := \frac{4}{9}\pi$; the right-most boundary is constructed as $\varphi = b := \frac{2}{9}\pi$ for $p \leq 0$ and

$$p(\varphi) = c\sqrt{\varphi - b}, \quad \varphi > b$$

for $p > 0$ such that the two parts join differentiably at $(\varphi, p) = (0, 0)$. The steepness of the curved part of the right-most boundary is governed by the constant $c$ (as seen in the two sinograms in Figure 3).

According to the condition (3.8), the curved part of $\text{bd}(\tilde{A})$ is the only part that can potentially cause object-independent artifacts in $D$, since the other parts are vertical. In Figure 3, we consider two data sets $\tilde{A}$ with smooth boundary; In Figure 3(A), the $x_b$-curve $\varphi \mapsto x_b(\tilde{\theta}(\varphi))$ is outside the unit disk and in Figure 3(B) it meets the object.

Figure 3(A) provides a reconstruction with data set defined by $c = 1.3$ in (4.2). Many artifacts in the reconstruction region are the same as in Figure 2 because the boundaries of the cutoff regions are substantially the same: the artifacts corresponding to the circles with $\varphi = 4\pi/9$ and the lower circle with $\varphi = 5\pi/9$ are the same limited-angle artifacts as in Figure 2 because those parts of the boundaries are the same. However, the upper right circled point in the sinogram has $\varphi > 5\pi/9$ so the corresponding artifact line has this larger angle, as seen in the reconstruction. The center reconstruction in Figure 3(A) shows the $x_b$-curve of artifacts, but it is far enough from $D$ that it is not visible in the reconstruction on the right.

Figure 3(B) provides a reconstruction with data set defined by $c = 0.65$ in (4.2). In this case, the object-dependent artifacts are similar to those in Figure 3(A) but the lines for $(\varphi, p)$ defined by (4.2) are different because $\text{bd}(\tilde{A})$ is different. The highlighted part of the boundary of $\tilde{A}$ defined by (4.2) indicates the boundary points that create the part of the $x_b$-curve of artifacts that now meets the reconstruction region. The highlighted curve in the right-hand reconstruction of Figure 3(B) is this part of the $x_b$-curve. Note that this curve is calculated using the formula (3.6) for $x_b(\tilde{\theta}(\varphi))$ rather than by visually tracing the physical curve on the reconstruction. That the calculated curve and the artifact curve are substantially the same shows the efficacy of our theory. A simple exercise shows that, for any $c > 0$, the $x_b$-curve changes direction at $x_b(\tilde{\theta}(1/2 + 5\pi/9))$.

Let $(\varphi_0, p_0)$ be the coordinates of the circled point in the upper right of the sinogram in Figure 3(B). This circled point is on the boundary of $\text{supp}(Rf)$ so $\tilde{L}(\varphi_0, p_0)$ is tangent to the skull and an object-dependent artifact is visible on $\tilde{L}(\varphi_0, p_0)$ in the reconstruction. The $x_b$-curve ends at $x_b(\tilde{\theta}(\varphi_0))$ (as justified by Theorem 3.4 B) and so the $x_b$-curve seems to blend into this line $\tilde{L}(\varphi_0, p_0)$. If $\text{supp}(f)$ were larger and the dotted part of the magenta curve on the sinogram were in $\text{supp}(Rf)$, the $x_b$-curve would be longer.

4.3. Region-of-interest (ROI) tomography. The ROI problem, also known as interior tomography, is a classical incomplete data tomography problem in which a part of the object (the ROI) is imaged using only data over lines that meet the ROI. Such ROI data are generated, e.g., when the detector width is not large enough to contain the complete object or when researchers would like a higher resolution scan of a small part of the object. In this section, we apply our theorems to understand ROI CT microlocally, including the ring artifact at the boundary of the ROI. We should point out that practitioners are well aware of the ring artifacts (see e.g., [7, 10]). Important related work has been done to analyze the ROI problem (e.g., [11, 12, 25, 28, 46, 50]).
(A) Left: Sinogram with the boundary of $\tilde{A}$ having large slope ($c = 1.3$). Center: FBP reconstruction over the larger region $[-2, 2]^2$ to show that the $x_b$-curve of artifacts is outside of the region displayed in the right frame. Right: Reconstruction highlighting object-dependent artifact lines tangent to the skull corresponding to the four circled points in the sinogram.

(B) Left: Sinogram with boundary of $\tilde{A}$ having small slope ($c = 0.65$). The part of the boundary causing the prominent $x_b$-curve of artifacts in the reconstruction region is highlighted in magenta. The solid part of the curve indicates the artifacts that are realized in the reconstruction. The dotted curve at the right end of the sinogram indicates potential artifacts that are not realized because the corresponding part of $\text{bd}(\tilde{A})$ is outside $\text{supp}(Rf)$ (see Theorem 3.4B). Center: FBP reconstruction. Right: Same FBP reconstruction as in the center image highlighting some of the added artifacts. The magenta curve in the reconstruction is the $x_b$-curve of artifacts and the yellow artifact lines are object-dependent artifacts similar to those in Figure 3(A).

**Figure 3.** Illustration of artifacts with smooth boundary given by (4.2). The $x_b$-curve $\varphi \mapsto x_b(\vartheta(\varphi))$ of artifacts is outside the reconstruction region in the top figure and it meets the object in the bottom picture.

First, note that Theorem 3.4C implies that all singularities of $f$ in the interior of the ROI are recovered. This is observed in Figure 4. If the ROI were not convex, then all singularities in the interior of its convex hull would be visible.

The boundary of the sinogram in Figure 4 is given by horizontal lines $p = \pm 0.8$. Since $p' = 0$, the $x_b$-curve (3.6) is given by $x_b(\vartheta(\varphi)) = 0.8 \cdot \vartheta(\varphi)$, which is a circle of radius $0.8$. The $x_b$-artifact-circle is highlighted in the right reconstruction of Figure 4, but it can be also be seen clearly in the top and bottom of the center reconstruction, even without the highlighting. However, the artifact circle does not extend outside the object (as represented by the dotted magenta curve in the reconstruction and which comes from the dotted segments of $\text{bd}(\tilde{A})$ in the sinogram) because
Figure 4. Left: ROI data taken within a disk of radius 0.8 centered at the origin, \( p \in [-0.8, 0.8] \). The boundary of \( \tilde{A} \) is highlighted in magenta. Center: FBP-reconstruction. Right Same FBP reconstruction as in the center image, highlighting the \( x_b \)-curve of artifacts in magenta and the object-dependent streak artifacts in yellow.

\( Rf \) is zero near the corresponding lines. Theorem 3.5 B. can be used to explain the invisible curve.

One also sees object-dependent artifacts described by Theorem 3.7 A. in Figure 4. For example, streak artifacts occur on the lines \( \tilde{L}(\varphi_0, p_0) \) corresponding to the four circled points \((\varphi_0, p_0)\) in \( \text{bd}(\tilde{A}) \) in the sinogram. These lines \( \tilde{L}(\varphi_0, p_0) \) are tangent to the outer boundary of the skull, therefore \( f \) has wavefront set directions normal to these lines, and this causes the artifacts by Theorem 3.7 A.

In general, one can show that if the ROI is strictly convex with smooth boundary then the \( x_b \)-curve of artifacts traces the boundary of the ROI. The proof is an exercise using the parametrization in \((\varphi, p)\) of tangent lines to this boundary.

4.4. The general case. The reconstruction in Figure 5 illustrates all of our cases in one. In that figure, we consider a general incomplete data set with a rectangular region cut out of the sinogram leading to all considered types of artifacts. Now, we describe the resulting artifacts. In Figure 5 the horizontal sinogram boundaries at \( p = p_0 = \pm 0.35 \) for \( \phi \in \left[ \frac{7}{18} \pi, \frac{11}{18} \pi \right] \) are displayed in solid magenta line. As in the ROI case, on these boundaries, we have \( p' = 0 \) and thus circular arcs of radius \( p_0 \) for the given interval for \( \varphi \) are added in the reconstruction (as indicated by solid magenta). As predicted by Theorem 3.7 C., each of the four corners produce a line artifact as marked by the yellow solid lines in the right-hand reconstruction, and they align tangentially with the ends of the curved artifacts.

The circular arc between those lines corresponds to the top and bottom parts of \( \text{bd}(\tilde{A}) \) as the data are, locally, constrained as in ROI CT (see Section 4.3).

In Figure 5 there are other object-dependent streaks corresponding to the vertical lines in the sinogram at \( \varphi = \frac{7}{18} \pi \) and at \( \varphi = \frac{11}{18} \pi \) as predicted by Theorem 3.7 A. but they are less pronounced and more difficult to see.

4.5. Summary. We have presented reconstructions that illustrate all of types of incomplete data and each of our theorems from Section 3. All artifacts arise because of points \((\varphi_0, p_0) \in \text{bd}(\tilde{A})\), and they fall into two categories.

- Streak artifacts on the line \( \tilde{L}(\varphi_0, p_0) \):
  - Object-dependent streaks occur when \( \text{bd}(\tilde{A}) \) is smooth at \((\varphi_0, p_0)\) and a singularity of \( f \) is normal to \( \tilde{L}(\varphi_0, p_0) \).
Figure 5. Left: The sinogram for a general incomplete data problem in which the cutoff region, $\tilde{A}$, has a locally smooth boundary with zero and infinite slope as well as corners. The cutout from the sinogram is at $\frac{7\pi}{18}$ and $\frac{11\pi}{18}$, $p = \pm 0.35$. Center: FBP reconstruction. Right: Same reconstruction with the circular $x_b$-curve of artifacts highlighted in magenta and object-independent “corner” streak artifacts highlighted in yellow.

- Object-independent streaks occur when $\text{bd}(\tilde{A})$ is nonsmooth at $(\varphi_0, p_0)$.
- Artifacts on curves are always object-independent, and they are generated by the map $\varphi \mapsto x_b(\vec{b}(\varphi))$ from parts of $\text{bd}(\tilde{A})$ that are smooth and of small slope.

5. Strength of added artifacts

In this section, we go back to parametrizing lines by $(\theta, p) \in S^1 \times \mathbb{R}$.

Using the Sobolev continuity of $Rf$, one can measure the strength in Sobolev scale of added artifacts in several useful cases. First, we define the Sobolev norm $\| \cdot \|_s$. We state it for distributions, therefore, it will apply to functions $f \in L^2_{\text{loc}}(D)$.

Definition 5.1 (Sobolev wavefront set [44]). For $s \in \mathbb{R}$, the Sobolev space $H_s(\mathbb{R}^n)$ is the set of all distributions with locally square-integrable Fourier transform and with finite Sobolev norm:

$$\| f \|_s := \left( \int_{y \in \mathbb{R}^n} |\mathcal{F} f(y)|^2 (1 + \|y\|^2)^s \, dy \right)^{1/2} < \infty.$$

Let $f$ be a distribution and let $x_0 \in \mathbb{R}^n$ and $\xi_0 \in \mathbb{R}^n \setminus 0$. We say $f$ is in $H^s$ at $x_0$ in direction $\xi_0$ if there is a cutoff function $\psi$ at $x_0$ and an open cone $V$ containing $\xi_0$ such that the localized and microlocalized Sobolev seminorm is finite:

$$\| f \|_{s, \psi, V} := \left( \int_{y \in V} |\mathcal{F} (\psi f)(y)|^2 (1 + \|y\|^2)^s \, dy \right)^{1/2} < \infty.$$

If (5.2) does not hold for any cutoff function at $x_0$, $\psi$, or any conic neighborhood $V$ of $\xi_0$, then we say that $(x_0, \xi_0)$ is in the Sobolev wavefront set of $f$ of order $s$, $(x_0, \xi_0) \in \text{WF}_s(f)$.

An exercise using the definitions shows that $\text{WF}(f) = \cup_{s \in \mathbb{R}} \text{WF}_s(f)$ (see [14]).

The Sobolev wavefront set can be defined for measurable functions $g$ on $S^1 \times \mathbb{R}$ using the identification (2.6) that reduces to this definition for $\vec{g}(\varphi, p) = g(\vec{b}(\varphi), p)$.

Note that this norm on distributions on $S^1 \times \mathbb{R}$ is not the typical $H_{0,s}$ norm used in elementary continuity proofs for the Radon transform (see e.g., [21] equation (2.11)), but this is the appropriate norm for the continuity theorems for general Fourier integral operators [22, Theorem 4.3.1], [9, Corollary 4.4.5].
Our next theorem gives the strength in Sobolev scale of added singularities of $\mathcal{L}_A f$ under certain assumptions on $f$. It uses the relation between microlocal Sobolev strength of $f$ and of $Rf$, [46, Theorem 3.1] and of $g$ and $R^* g$, which is given in Proposition [A.6] (see also [28] for related results).

**Theorem 5.2.** Let $f \in L^2(D)$ and let $A \subset S^1 \times \mathbb{R}$ satisfy Assumption [3.1]. Let $(\theta_0, p_0) \in \text{bd}(A)$ and assume $Rf(\theta_0, p_0) \neq 0$ and $f$ is smooth normal to $L(\theta_0, p_0)$, i.e., $\text{WF}_{L(\theta_0, p_0)}(f) = \emptyset$.

A. Assume $\text{bd}(A)$ is smooth and not vertical at $(\theta_0, p_0)$. Let $x_b = x_b(\theta_0)$ be given by (3.6) and let $\omega \neq 0$. Then, $\mathcal{L}_A f$ is in $H_s$ for $s < 0$ at $\xi_0 = (x_b, \omega b(\theta_0))$ and $\xi_0 \in \text{WF}_0(\mathcal{L}_A f)$. Thus, there are singularities above $x_b$ in the 0-order wavefront set of $\mathcal{L}_A f$.

B. Now, assume $\text{bd}(A)$ has a corner at $(\theta_0, p_0)$ (see Definition [3.2]). Then for each $(x, \xi) \in N(L(\theta_0, p_0))$, $(x, \xi) /\in \text{WF}_1(\mathcal{L}_A f)$ and, except for two points on $L(\theta_0, p_0)$, $\mathcal{L}_A f$ is in $H_s$ for $s < 1$ at $(x, \xi)$. If one of the two one-sided tangential lines to the corner is vertical, then there is only one such point.

This theorem provides estimates on smoothness for more general data sets than the limited-angle case, which was thoroughly considered in [24][25]. In contrast to part A of this theorem, if $\text{bd}(A)$ has a vertical tangent at $(\theta_0, p_0)$, then, under the smoothness assumption on $f$, there are no added artifacts in $\mathcal{L}_A f$ normal to $L(\theta_0, p_0)$ (see Theorem [3.7A]). Part A of this theorem is a more precise version of Theorem [3.5][3]. Under the assumptions in parts A and B, $\text{bd}(A)$ will cause specific singularities in specific locations on $L(\theta_0, p_0)$. The two more singular points in part B are specified in equation [A.15]. If one part of $\text{bd}(A)$ is vertical at $(\theta_0, p_0)$, then there is only one such more singular point.

This theorem will be proven in Section [A.3] of the appendix.

### 6. Artifact Reduction

In this section, we briefly describe a method to suppress the added streak artifacts described in Theorems [3.5] and [3.7]. This is a standard technique for many practitioners, but it is worth Highlighting because it is simple and useful.

As outlined in Section [3], the application of FBP to incomplete data extends the data from $A \subset S^1 \times \mathbb{R}$ to all of $S^1 \times \mathbb{R}$ by padding it with zeros on the complement of $A$. This hard truncation can create discontinuities on $\text{bd}(A)$ and that explains the artifacts. These jumps are stronger singularities than those of $Rf$ for $Rf \in H_{1/2}(S^1 \times \mathbb{R})$ since $f \in L^2(D) = H_0(D)$.

One natural way to get rid of the jump discontinuities of $\mathbb{1}_A$ is to replace $\mathbb{1}_A$ by a smooth function on $S^1 \times \mathbb{R}$, $\psi$, that is equal to zero off of $A$ and equal to one on most of $\text{int}(A)$ and smoothly transitions to zero near $\text{bd}(A)$. We also assume $\psi$ is symmetric in the sense $\psi(\theta, p) = \psi(-\theta, -p)$ for all $(\theta, p)$. This gives the forward operator

$$R_{\psi} f(\theta, p) = \psi(\theta, p) R f(\theta, p)$$

and the reconstruction operator

$$\mathcal{L}_{\psi} f = R^* (\Lambda R_{\psi} f) = R^* (\Lambda \psi R f).$$

Because $\psi$ is a smooth function, $R_{\psi}$ is a standard Fourier integral operator and so $\mathcal{L}_{\psi}$ is a standard pseudodifferential operator. This allows us to show that $\mathcal{L}_{\psi}$ does not add artifacts.

**Theorem 6.1** (Artifact Reduction Theorem). Let $f \in L^2(D)$ and let $A \subset S^1 \times \mathbb{R}$ satisfy Assumption [3.1]. Then

$$\text{WF}(\mathcal{L}_{\psi} f) \subset \text{WF}(f).$$

Therefore, $\mathcal{L}_{\psi}$ does not add artifacts to the reconstruction.

Let $x \in D$, $\theta \in S^1$, and $\omega \neq 0$. If $\psi(\theta, x \cdot \theta) \neq 0$, then

$$\text{WF}(\mathcal{L}_{\psi} f) \subset \text{WF}(f).$$
Figure 6. Left: Smoothed sinogram. Center: Smoothed reconstruction with suppressed artifacts. Right: Reconstruction using $\mathcal{L}_A$, with sharp cutoff.

Theorem 6.1 is a special case of a known result in e.g., [28] or the symbol calculation in [45] and is stated for completeness. This theorem shows the advantages of including a smooth cutoff, and it has been suggested in several settings, including limited-angle X-ray CT [15, 24] and more general tomography problems [16, 17, 28, 53]. More sophisticated methods are discussed in [5, 6] for the synchrotron problem that is described in Section 7.

Although this artifact reduction technique does not create any singular artifacts in $\mathcal{L}_\psi f$, it can turn singular artifacts into smooth artifacts, for example, by smoothing $x_b$-curves.

Figure 6 illustrates the efficacy of this smoothing algorithm on simulated data, and Figure 9 in Section 7 demonstrates its benefits on real synchrotron data.

7. APPLICATION: A SYNCHROTRON EXPERIMENT

In this section, we use the identifications given in (4.1) and show sinograms as subsets of the $(\varphi; p)$ plane.

Figure 7. Left: The truncated attenuation sinogram (after processing to get Radon transform data). Center: the enlargement of the section of $\text{bd}(\tilde{A})$ between the two dark vertical lines in the left-hand sinogram. Right: Zoom of the corresponding reconstruction. [5, ©IOP Publishing. Reproduced by permission of IOP Publishing. All rights reserved].

Figure 7 shows tomographic data of a chalk sample (sinogram on the left and a zoomed version in the center) that was acquired by a synchrotron experiment [5, 6] (see [29] for related work). In the
right picture of Figure 7, a zoom of the corresponding reconstruction is shown (see also Figure 9(A)). As can be clearly observed, the reconstruction includes dramatic streaks that are independent of the object. These streaks motivated the research in this article since they were not explained by the mathematical theory at that time (such as in \[15,17,24,35\]).

Figure 2: Left: Side-view of the percolation cell. Right: Top-view of the setup, where the position of sample metal bar.

Figure 8. Data acquisition setup for the synchrotron experiment \[5\] \copyright IOP Publishing. Reproduced by permission of IOP Publishing. All rights reserved.

Taking a closer look at the attenuation sinogram and its zoom in Figure 7, a staircasing is revealed with vertical and horizontal boundaries. This is a result of X-rays being blocked by four metal bars that help stabilize the percolation chamber (sample holder) as the sample is subjected to high pressure during data acquisition, see Figure 8. More details are given in \[5\].

Discussion

8.1. Observations. The proofs of Theorems 3.5 and 3.7 show that if \((\theta_0, p_0) \in \text{bd}(A)\) and \(\text{WF}(\mathbb{I}_ARf) = T^*(S^1 \times \mathbb{R}) \setminus 0\), then \(\mathcal{L}_A f\) will have a streak all along \(L(\theta_0, p_0)\). The analogous theorem for Sobolev singularities, Theorem 5.3, assumes that \(A\) has a corner at \((\theta_0, p_0)\). If \(A\) has a weaker singularity at \((\theta_0, p_0)\), then an analogous theorem would hold but one would need to factor in the Sobolev strength of the wavefront of \(\mathbb{I}_A\) above \((\theta_0, p_0)\).

The artifact reduction method, which is motivated by Theorem 6.1, works well for the synchrotron data as was shown in Figure 9 in Section 7. The article \[5\] provides more elaborate artifact reduction methods that are even more successful for this particular problem. We point out that this simple technique might not work as efficiently in other incomplete data tomography problems as in the problems we present. Nevertheless, our theorems and experiments show that abrupt cutoffs that add new singularities in the sinogram should be avoided.

There are other methods to deal with incomplete data. For example, data completion using the range conditions for the Radon transform has been developed, e.g., in \[2,30,56\]. In \[38\] and \[8,41\], the authors develop artifact reduction methods for quantitative susceptibility mapping. For metal artifacts, there is vast literature (see, e.g., \[3\]) for artifact reduction methods, and we believe that those methods might also be useful for certain other incomplete data tomography problems. In \[39,43,51\], the authors have effectively used microlocal analysis to understand these related problems.
Our theory is developed based on the continuous case – we view the data as functions on $S^1 \times \mathbb{R}$, not just defined at discrete points. As shown in this article, our theory predicts and explains the artifacts and visible and invisible singularities. In practice, real data are discrete, and discretization may also introduce artifacts, such as undersampling streaks. Discretization in our synchrotron experiment could be a factor in the streaks in Figure 7 in Section 7. Furthermore, numerical experiments have finite resolution, and this can cause (and sometimes de-emphasize) artifacts. For all these reasons, further analysis is needed to shed light on the interplay between the discrete and the continuous theory for CT reconstructions from incomplete data.

8.2. Generalizations. Theorems 3.5 and 3.7 were proven for $\mathcal{L}_A = R^* (\Lambda (I_A R))$, but the results hold for any filtering operator that is elliptic in the sense of Remark A.5. This is true because that ellipticity condition is all we used about $\Lambda$ in the proofs. For example, the operator, $L = -\frac{\partial^2}{\partial p^2}$, in Lambda CT [12] satisfies this condition, and the only difference comes in our Sobolev Continuity
Theorem 5.2 Since \( L \) is order two, the operator \( R^*LR \) is of order 1 and the smoothness in Sobolev scale of the reconstructions would be one degree lower than for \( \mathcal{L}_A \).

Our theorems hold for fan-beam data when the source curve \( \gamma \) is smooth and convex and the object is compactly supported inside \( \gamma \). This is true because, in this case, the fan-beam parameterization of lines is diffeomorphic to the parallel-beam parametrization we use and the microlocal theorems we use are invariant under diffeomorphisms. However, one needs to check that the parallel-beam data set satisfies Assumption 3.1.

Theorems 3.5 and 3.7 hold verbatim for generalized Radon transforms with smooth measures on lines in \( \mathbb{R}^2 \) because they all have the same canonical relation, given by \( (A.4) \), and the proofs would be done as for \( \mathcal{L}_A \) but using the basic microlocal analysis in \[45\].

Analogous theorems hold for other Radon transforms including the generalized hyperplane transform, the spherical transform of photoacoustic CT, and other transforms satisfying the Bolker assumption \( (A.7) \). The proofs would use our arguments here plus the proofs in \[16, 17\]. These generalizations are the subject of ongoing work. In incomplete data problems for \( R \), the artifacts are either on \( x_b \)-curves or they are streaks on the lines corresponding to points on \( \partial(\mathcal{A}) \). However, in higher-dimensional cases, the results will be more subtle because artifacts can spread on proper subsets of the surface over which data are taken, not necessarily the entire set (see \[16\] Remark 4.7).

Analogous theorems should hold for cone-beam CT, but this type of CT is more subtle because the reconstruction operator itself can add artifacts, even with complete data \[13, 18\].

Appendix A. Proofs

We now provide some basic microlocal analysis and then use this to prove our theorems. We adapt the standard terminology of microlocal analysis and consider wavefront sets as subsets of \( \mathbb{R}^2 \) because they all have the same canonical relation, given by \( (A.4) \), and the proofs would be done as for \( \mathcal{L}_A \) but using the basic microlocal analysis in \[45\].

Standard references include \[14, 55\]. Elementary presentations of microlocal analysis for tomography are in \[26, 27\].

A.1. Building blocks. Our first lemma gives some basic facts about wavefront sets.

**Lemma A.1.** Let \( x_0 \in \mathbb{R}^2 \). Let \( u \) and \( v \) be locally integrable functions or distributions.

A. Let \( U \) be an open neighborhood of \( x_0 \). Assume that \( u \) and \( v \) are equal on \( U \), then \( \WF_{x_0}(u) = \WF_{x_0}(v) \).

B. If \( u \) and \( \psi \) are both in \( L^1_{\text{loc}} \) and \( \psi \) is smooth near \( x_0 \), then \( \WF_{x_0}(u) \subseteq \WF_{x_0}(\psi u) \). If, in addition, \( \psi \) is nonzero at \( x_0 \) then \( \WF_{x_0}(u) \subseteq \WF_{x_0}(\psi u) \).

C. \( \WF_{x_0}(u) = \emptyset \) if and only if there is an open neighborhood \( U \) of \( x_0 \) on which \( u \) is a smooth function.

The analogous statements hold for functions on \( S^1 \times \mathbb{R} \).

These basic properties are proven using the arguments in Section 8.1 of \[23\], in particular, Lemma 8.1.1, Definition 8.1.2, and Proposition 8.1.3. This lemma is valid for functions on \( S^1 \times \mathbb{R} \) using the identifications of \( S^1 \times \mathbb{R} \) with \( \mathbb{R}^2 \) given by \( (2.5) \) and for functions \( (2.6) \) and the fact that singularities are defined locally.

Our next definition will be useful to describe how wavefront sets transform under \( R \) and \( R^* \).

**Definition A.2.** Let \( C \subset T^*(S^1 \times \mathbb{R}) \times T^*(\mathbb{R}^2) \) and let \( B \subset T^*(\mathbb{R}^2) \). The composition is defined

\[
C \circ B = \{ (\theta, p, \eta) \in T^*(S^1 \times \mathbb{R}) : (\theta, p, \eta, x, \xi) \in C \text{ for some } (x, \xi) \in B \}.
\]

We define \( C^t = \{ (x, \xi, \theta, p, \eta) : (\theta, p, \eta, x, \xi) \in C \} \).

The function \( g \) on \( S^1 \times \mathbb{R} \) will be called symmetric if

\[
(A.1) \quad \forall (\theta, p) \in S^1 \times \mathbb{R}, \quad g(\theta, p) = g(-\theta, -p).
\]
If $f \in L^2(D)$, then $Rf$ and $\Lambda_{A}Rf$ are both locally integrable functions are symmetric in this sense. For such functions,

(A.2) \((\theta_0, p_0, \omega_0(-\alpha d\theta + dp)) \in \WF(g) \iff (-\theta_0, -p_0, -\omega_0(\alpha d\theta + dp)) \in \WF(g)\).

For these reasons, we will identify cotangent vectors

(A.3) \((\theta_0, p_0, \omega_0(-\alpha d\theta + dp)) \iff (-\theta_0, -p_0, -\omega_0(\alpha d\theta + dp))\).

Our next proposition is the main technical theorem of the article. It provides the wavefront correspondences for $R$ and $R^*$ which we will use in our proofs.

**Proposition A.3** (Microlocal correspondence of singularities). The X-ray transform, $R$, is an elliptic Fourier integral operator (FIO) with canonical relation

\[
C = \left\{ \left( \theta, x \cdot \theta, \omega(-x \cdot \theta^1 d\theta + dp), x, \omega \theta dx \right) : \theta \in S^1, x \in \mathbb{R}^2, \omega \neq 0 \right\}.
\]

Let $f \in L^2(D)$ and let $g$ be a locally integrable function on $S^1 \times \mathbb{R}$ that is symmetric by (A.1). Let $x_0 \in \mathbb{R}^2$, $\theta_0 \in S^1$, and let $p, \alpha$, and $\omega$ be real numbers with $\omega \neq 0$.

The X-ray transform $R$ is an elliptic FIO with canonical relation $C$. Therefore,

\[
\WF(Rf) = C \circ WF(f) \quad \text{and}
\]

(A.5)

\[
C \circ \{(x_0, \omega \theta dx)\} = \left\{ \left( \theta_0, x_0 \cdot \theta_0, \omega(-x_0 \cdot \theta_0^1 d\theta + dp) \right) \right\}
\]

under the identification (A.3).

The dual transform $R^*$ is an elliptic FIO with canonical relation $C^t$. Then,

\[
WF(R^*g) = C^t \circ WF(g) \quad \text{and}
\]

(A.6)

\[
C^t \circ \{(\theta, p, \omega(-\alpha d\theta + dp))\} = \{(x_0(\theta, p, \alpha), \omega \theta dx)\}
\]

where $x_0(\theta, p, \alpha) = \alpha \theta^1 + p\theta$.

Here are pointers to the elements of this proof. The facts about $R$ are directly from [46, Theorem 3.1] or [48, Theorem A.2], and they use the calculus of the FIO $R$ [19,20] (see also [45]). Note that the crucial point is that $R$ is an elliptic Fourier integral operator that satisfies the global Bolker assumption: the natural projection

(A.7) \[ \Pi_L : C \to T^*(Y) \]

is an injective immersion,

so (A.5) holds for $R$. A straightforward calculation using (A.4) shows that the global Bolker assumption holds. Note that we are using the identification (A.3) in asserting that (A.5) is an equality. The proofs for $R^*$ are parallel to those for $R$ except they involve the canonical relation for $R^*$, $C^t$, rather than $C$.

**Remark A.4.** In [16,17] the authors prove artifact characterizations for limited data problems for photoacoustic CT and generalized hyperplane transforms. One key is a fundamental result on multiplying distributions, [23, Theorem 8.2.10]. If $u$ and $v$ are distributions on $S^1 \times \mathbb{R}$, this theorem implies they can be multiplied as distributions if they satisfy the non-cancellation condition $\forall (\theta, p, \eta) \in WF(u), (\theta, p, -\eta) \notin WF(v)$. Then $uv$ is a distribution and an upper bound for $WF(uv)$ is given in terms of $WF(u)$ and $WF(v)$.

However, this non-cancellation condition does not hold for $\Lambda_A$ and $Rf$ when $\Lambda_A$ either is smooth with small slope or is not smooth at $\theta_0, p_0$. That is why we consider functions $f \in L^2(D)$ in this article since $\Lambda_A Rf$ will be a function in $L^2(S^1 \times \mathbb{R})$ even if [23, Theorem 8.2.10] does not apply.

Our next remark will be used in ellipticity proofs that follow.
Remark A.5. The operator $\Lambda$ is elliptic in all cotangent directions except $d\theta$ because the symbol of $\Lambda$ is $|\tau|$ where $\tau$ is the Fourier variable dual to $p$. However, the $d\theta$ direction will not affect our proofs. This is true because, for any function $f \in L^2(D)$, the covector $(\theta, p, \omega d\theta)$ is not in $WF(Rf)$ because $WF(Rf) = C \circ WF(f)$ (use the definition of composition and (A.4)). So, for each $f \in L^2(D)$, $WF(\Lambda f) = WF(Rf)$. Because $C^t \circ \{(\theta, p, \omega d\theta)\} = \emptyset$ by (A.4), even if $(\theta, \omega d\theta) \in WF(\Lambda f)$, that covector will not affect the calculation of $C^t \circ WF(\Lambda f)$. Therefore, $\Lambda$ is elliptic on all cotangent directions that are preserved when composed with $C^t$, and these are all the directions we need in our proofs.

Our theorems will be valid for any pseudodifferential operator on $S^1 \times \mathbb{R}$ that is invariant under the symmetry condition (A.1) and satisfies this ellipticity condition (although the Sobolev results will depend on the order of the operator).

A.2. Proof of Theorems 3.5, 3.7, and 3.9. In the proofs of these theorems, we use Proposition A.3 to analyze how multiplication by $\Lambda f$ adds singularities to the data $Rf$ and then to the reconstruction, $\mathcal{L}_f f$. We first make observations that will be useful in the proofs.

Let $A$ satisfy Assumption 3.1 and let $f \in L^2(D)$. Let

$$G = \mathcal{I}_A Rf \quad \text{then} \quad R^* \Lambda G = \mathcal{L}_f f.$$  

By Remark A.5 and the statements in Proposition A.3

$$(A.8) \quad \text{WF}(\mathcal{L}_f f) = C^t \circ \text{WF}(G).$$

Using the expression (A.4) for $C$, one can show for $(\theta_0, p_0) \in S^1 \times \mathbb{R}$ that

$$C \circ (N^*(L(\theta_0, p_0)) \setminus 0) = T_{(\theta_0, p_0)}^*(S^1 \times \mathbb{R}) \setminus P$$

where

$$(A.9) \quad N^*(L(\theta_0, p_0)) = \{(x, \omega_0 dx) : x \in L(\theta_0, p_0), \omega \in \mathbb{R}\}$$

and

$$P = \{(\theta, p, \omega d\theta) : (\theta, p) \in S^1 \times \mathbb{R}, \omega \in \mathbb{R}\}.$$  

Because $WF(Rf) = C \circ WF(f)$, (A.9) implies that if $f$ is smooth conormal to $L(\theta_0, p_0)$, then $Rf$ is smooth near $(\theta_0, p_0)$.

Using analogous arguments for $C^t$, one shows for $(\theta, p) \in S^1 \times \mathbb{R}$ that

$$(A.10) \quad C^t \circ (T_{(\theta, p_0)}^*(S^1 \times \mathbb{R}) \setminus 0) = N^*(L(\theta_0, p_0)) \setminus 0.$$  

By (A.8), if $G$ is smooth near $(\theta_0, p_0)$ then $\mathcal{L}_f f$ is smooth conormal to $L(\theta_0, p_0)$.

To start the proofs, let $f \in L^2(D)$ and let $A$ be a data set satisfying Assumption 3.1. Theorem 3.4 establishes that if $(\theta_0, p_0) \notin bd(A)$, then there are no artifacts in $\mathcal{L}_f f$ conormal to $L(\theta_0, p_0)$ (since $WF_L(\theta_0, p_0)(\mathcal{L}_f f) \subset WF_L(\theta_0, p_0)(f)$). Therefore, the only singular artifacts are on lines $L(\theta_0, p_0)$ for $(\theta_0, p_0) \in bd(A)$.

Proof of Theorem 3.5. Assume $bd(A)$ is smooth with finite slope at $(\theta_0, p_0)$. Therefore, there is an open neighborhood $I$ of $\theta_0$ and a smooth function $p = p(\theta)$ for $\theta \in I$ such that $(\theta, p(\theta)) \in bd(A)$. A straightforward calculation shows for each $\theta \in I$ and each $\omega \neq 0$ that

$$(A.11) \quad \eta(\theta) = (\theta, p(\theta), \omega(-p'(\theta)d\theta + dp))$$

is conormal to $bd(A)$ at $(\theta, p(\theta))$. A calculation using (A.6) and (A.8) shows that

$$(A.11) \quad \eta(\theta) \in WF(G) \quad \text{if and only if} \quad (x_0(\theta), \omega d\theta dx) \in WF(\mathcal{L}_f f),$$

where $x_0(\theta)$ is given by (3.6). Then, $(x_0(\theta), \omega_0 d\theta dx)$ is the possible object-independent artifact that could occur on $L(\theta_0, p_0)$. Note that $x_0(\theta)$ is simply the $x$-projection of $C^t \circ N^*(bd(A))$.

By taking the derivative $x'_0(\theta)$, one can show that the only case in which the $x_0$-curve is a subset of a line occurs when $bd(A)$ is locally defined by lines through a point (e.g., for some $x_0 \in \mathbb{R}^2$,}
bd(A) is locally given by \( p(\theta) = x_0 \cdot \theta \). However, in this case \([3.6]\) shows that the \( x_0 \)-curve is the single point \( x_0 \). This proves part A.

If \( f \) has no singularities conormal to \( L(\theta_0, p_0) \), then \( Rf \) is smooth near \( (\theta_0, p_0) \), so \( \text{WF}(\theta_0, p_0))(G) \subseteq \text{WF}(\theta_0, p_0))(L_A) \) by Lemma \( A.1[B] \). This proves part B. \( \square \)

Proof of Theorem 3.7. To prove part A, we make a simple observation. Singularities of \( f \) conormal to \( L(\theta_0, p_0) \) can cause singularities in \( G \) only above \( (\theta_0, p_0) \) and those can cause singularities of \( L_A f \) conormal to \( L(\theta_0, p_0) \) (and nowhere else).

Part B follows from the fact that the conormal to \( \text{bd}(A) \) at \( \theta_0 \) is \( \omega d\theta \) for \( \omega \neq 0 \), that \( C^t \circ \{(\theta, p, \omega d\theta) = 0, \text{ and the arguments in the proof of Theorem 3.5 B.(1).} \)

Now, we assume \( \text{bd}(A) \) is not smooth at \( (\theta_0, p_0) \).

The first observation is straightforward: if \( \text{bd}(A) \) is not smooth at \( (\theta_0, p_0) \), then that singularity can cause singularities in \( G \) at \( (\theta_0, p_0) \) which cause singularities of \( L_A f \) conormal to \( L(\theta_0, p_0) \) (and nowhere else).

Assume \( f \) is smooth conormal to \( L(\theta_0, p_0) \), \( Rf(\theta_0, p_0) \neq 0 \), and \( A \) has a corner at \( (\theta_0, p_0) \) (see Definition 3.2). Then, by Lemma A.1, \( \text{WF}(\theta_0, p_0))(G) = \text{WF}(\theta_0, p_0))(L_A) \) which is equal to \( T^*(\theta_0, p_0)(S^1 \times \mathbb{R}) \setminus 0 \). Therefore, by \([A.10]\), \( \text{WF}_{L(\theta_0, p_0)}(L_A f) \) = \( N^*(L(\theta_0, p_0)) \setminus 0 \). This finishes the proof of Theorem 3.7 \( \square \)

Proof of Theorem 3.9. Let \( f \in L^2(D) \) and assume \( A \) satisfies Assumption \([3.1]\). Theorem 3.4 establishes that artifacts are added in \( L_A f \) conormal to \( L(\theta_0, p_0) \) only when \( (\theta_0, p_0) \in \text{bd}(A) \). Let \( (\theta_0, p_0) \in \text{bd}(A) \). Singularities of \( G = I_A Rf \) at \( (\theta_0, p_0) \) come only from singularities of \( I_A \) or singularities of \( Rf \) at \( (\theta_0, p_0) \). Therefore, singularities of \( L_A f \) conormal to \( L(\theta_0, p_0) \) come only from singularities of \( I_A \) at \( (\theta_0, p_0) \) or singularities of \( Rf \) at \( (\theta_0, p_0) \).

The artifacts of \( L_A f \) caused by \( I_A \) are analyzed in the proof of Theorem 3.5 and Theorem 3.7 parts B and C. The artifacts of \( L_A f \) caused by \( Rf \) are covered in Theorem 3.7 A. This takes care of all singular artifacts for the continuous problem. \( \square \)

A.3. Proof of Theorem 5.2. We first prove a proposition giving the correspondence between Sobolev wavefront set and \( R^* \).

Proposition A.6 (Sobolev wavefront correspondence for \( R \) and \( R^* \)). Let \( (\theta_0, p_0) \in S^1 \times \mathbb{R}, \omega_0 \neq 0, \) and let \( s \) and \( \alpha \) be real numbers. Let

\[
\eta_0 = \omega_0(-\alpha d\theta + dp), \quad x_0 = p_0 \theta_0 + \alpha \theta_0^+ \text{, and } \xi_0 = \omega_0\theta_0dx.
\]

Let \( f \) be a distribution on \( \mathbb{R}^2 \) and \( g \) a distribution on \( S^1 \times \mathbb{R} \). Then,

\[
\begin{align*}
(A.12) \quad & (x_0, \xi_0) \in \text{WF}_s(f) \iff (\theta_0, p_0, \eta_0) \in \text{WF}_{s+1/2}(Rf), \\
(A.13) \quad & (\theta_0, p_0, \eta_0) \in \text{WF}_{s}(g) \iff (x_0, \xi_0) \in \text{WF}_{s+1/2}(R^*g).
\end{align*}
\]

Proof. Equivalence \([A.12] \) is given \([46]\) Theorem 3.1], however the proof of the \( \Rightarrow \) implication for \( R \) was left to the reader.

The proof of the \( \Rightarrow \) implication of \([A.13] \) is completely analogous to the proof given in \([46]\) for \( R \). For completeness, we will prove the \( \Leftarrow \) implication of \([A.13] \). Assume \( g \) is in \( H_s \) at \( (\theta_0, p_0, \eta_0) \). By \([44]\) Theorem 6.1, p. 259], we can write \( g = g_1 + g_2 \) where \( g_1 \in H_s \) and \( (\theta_0, p_0, \eta_0) \notin \text{WF}(g_2) \). The operator \( R^* \) is continuous in Sobolev spaces from \( H_s \) to \( H_{s+1/2} \) by \([55]\) Theorem VIII 6.1 since \( C^t \) is a local canonical graph. Therefore \( R^*g_1 \in H_{s+1/2} \). Since \( (\theta_0, p_0, \eta_0) \notin \text{WF}(g_2), (x_0, \xi_0) \notin \text{WF}(R^*g_2) \)


by the wavefront correspondence (A.6). An exercise using Definition 5.1 and the Fourier transform shows that $R^*g = R^*g_1 + R^*g_2$ is in $H_{s+1/2}$ at $(x_0, \xi_0)$.

**Proof of Theorem 5.2.** Let $f \in L^2(D)$ and let $A$ satisfy Assumption 3.1. Let $(\theta_0, p_0) \in \text{bd}(A)$ and assume $Rf(\theta_0, p_0) \neq 0$ and $f$ is smooth conormal to $L(\theta_0, p_0)$. Because $f$ is smooth conormal to $L(\theta_0, p_0)$, $WF_{(\theta_0, p_0)}(Rf) = \emptyset$ so $Rf$ is smooth in a neighborhood of $(\theta_0, p_0)$ by Lemma A.1.C. Since $Rf(\theta_0, p_0) \neq 0$, for each $s$,

$$\text{(WF}_{s-1}(\theta_0, p_0) (\Lambda \mathbb{1}_ARf) = (WF_s)(\theta_0, p_0) (\mathbb{1}_ARf) = (WF_s)(\theta_0, p_0) (\mathbb{1}_A);$$

the left-hand equality is true because $\Lambda$ is an elliptic pseudodifferential operator of order one (except in the irrelevant direction $d\theta$—see Remark A.4), and the right-hand equality is true by Lemma A.1.B.

To prove part A of the theorem, assume $\text{bd}(A)$ is smooth and has finite slope at $(\theta_0, p_0)$. Because the Sobolev wavefront set is contravariant under diffeomorphism [55], we may assume $\text{bd}(A)$ is a horizontal line, at least locally near $(\theta_0, p_0)$. Let $\eta_0 = dp$. We claim that $(\theta_0, p_0, \pm \eta_0) \in WF_{1/2}(\mathbb{1}_A)$ and, for $s < 1/2$, $\mathbb{1}_A$ is in $H_s$ at $(\theta_0, p_0, \pm \eta_0)$. Furthermore $\mathbb{1}_A$ is smooth in every other direction above $(\theta_0, p_0)$. The proofs of these two statements are now outlined. Using a product cutoff function $\psi = \psi_1(\theta)\psi_2(p)$ to calculate $\mathcal{F}(\psi \mathbb{1}_A)$ and integrations by parts, one can show that this localized Fourier transform is of the form $S(\nu)T(\tau)$ where $S$ is a smooth, rapidly decreasing function and $T$ is $O(1/|\tau|)$ (and not $O(1/|\tau|^p$ for any $p > 1$). Therefore $S(\nu)T(\tau)$ is rapidly decaying in all directions but the vertical. This implies that $\mathbb{1}_A$ is in $H_s$ for $s < 1/2$ at $(\theta_0, p_0, \pm \eta_0)$ and $(\theta_0, p_0, \pm \eta_0) \in WF_{1/2}(\mathbb{1}_A)$. This also shows that this localized Fourier transform is rapidly decaying in all directions except $\pm \eta_0$. Now, using (A.14) one sees that $(\theta_0, p_0, \pm \eta_0) \in WF_{-1/2}(\Lambda \mathbb{1}_ARf); \Lambda \mathbb{1}_ARf$ is in $H_s$ for $s < -1/2$ at $(\theta_0, p_0, \pm \eta_0)$; and $(\theta_0, p_0, \eta) \notin WF(\Lambda \mathbb{1}_ARf)$ for any $\eta$ not parallel to $\eta_0$.

Now, by Proposition A.6 $\mathcal{L}_Af = R^*\Lambda \mathbb{1}_ARf$ is in $H_s$ at $(x_0(\theta_0), \pm \theta_0dx)$ for $s < 0$ and

$$(x_0(\theta_0), \pm \theta_0dx) \in WF_{0}(\mathcal{L}_Af),$$

where $x_0(\theta_0)$ is given by (3.6). Using this theorem again, one sees that for any $x \in L(\theta_0, p_0)$, if $x \neq x_0(\theta_0)$

$$(x, \pm \theta_0dx) \notin WF(\mathcal{L}_Af).$$

Therefore, the only covectors in $N^*(L(\theta_0, p_0)) \cap WF(\mathcal{L}_Af)$ are $(x_0(\theta_0), \alpha \theta_0dx)$ for $\alpha \neq 0$.

To prove part B, assume $\text{bd}(A)$ has a corner at $(\theta_0, p_0)$. Let $\alpha_1$ and $\alpha_2$ be the slopes at $(\theta_0, p_0)$ of the two parts of $\text{bd}(A)$. Let

$$(\eta_j = -\alpha_j d\theta + dp, \quad x_{b_j} = p_0 \theta_0 + \alpha_j \theta_0^0, \quad j = 1, 2.$$  

An argument similar to the diffeomorphism/integration by parts argument in the last part of the proof is used. First a diffeomorphism is used to transform the corner so, locally $A$ becomes $\bar{A} = \{(\theta, p) : \theta \geq 0, p \geq 0\}$. To do this, one uses Definition 3.2 and footnote 4 and the Inverse and Implicit Function Theorems. Then one uses a product cutoff $\psi = \psi_1(\theta)\psi_2(p)$ to calculate $\text{WF}_{s}((1_p\pi))$ at $(0, 0)$. Then, the Fourier transform can be written $\mathcal{F}(\psi \mathbb{1}_{\bar{A}}) = S(\nu)T(\tau)$ where $S(\nu) = O(1/|\nu|)$ and $T(\tau) = O(1/|\tau|)$. So, the localized Fourier transform is decreasing of order $-1$ in the dp (vertical) and $d\theta$ (horizontal) directions and $-2$ in all other directions.

Note that $\eta_1$ and $\eta_2$ are the images of dp and $d\theta$ under the diffeomorphism back to the original coordinates. By contravariance of Sobolev wavefront set under diffeomorphism and the assumption that $Rf$ is smooth and nonzero near $(\theta_0, p_0), (\theta_0, p_0, \pm \eta_j) \in WF_{-1/2}(\Lambda \mathbb{1}_ARf)$ and, for $s < -1/2$, $\Lambda \mathbb{1}_ARf$ is in $H_s$ at $(\theta_0, p_0, \eta_j)$. Other covectors are in $WF_{1/2}(\Lambda \mathbb{1}_ARf)$. One finishes the proof using (A.13).

This proof shows for $j = 1, 2$ that $C^t \circ \{(\theta_0, p_0, \eta_j)\} \in WF_{0}(\mathcal{L}_Af)$, and these are the “more singular points” referred to after the statement of Theorem 5.2. If one part of $\text{bd}(A)$ is vertical at
(θ₀, p₀), then for one value of j, ηᵢ is parallel to dθ and Cᵗ ∘ {⟨θ₀, p₀, ηᵢ⟩} = ∅ so there is only one point, not two, on L(θ₀, p₀) on which f is more singular.

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