EXTENSIONS OF THE HEISENBERG-WEYL INEQUALITY

H. P. HEINIG and M. SMITH

Department of Mathematical Sciences McMaster University Hamilton, Ontario L8S 4K1, Canada

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ABSTRACT. In this paper a number of generalizations of the classical Heisenberg-Weyl uncertainty inequality are given. We prove the n-dimensional Hirschman entropy inequality (Theorem 2.1) from the optimal form of the Hausdorff-Young theorem and deduce a higher dimensional uncertainty inequality (Theorem 2.2). From a general weighted form of the Hausdorff-Young theorem, a one-dimensional weighted entropy inequality is proved and some weighted forms of the Heisenberg-Weyl inequalities are given. KEY WORDS AND PHRASES. Uncertainty Inequality, Fourier Transform, Variance, Entropy Hausdorff-Young Inequality, Weighted Norm Inequalities. 1980 AMS SUBJECT CLASSIFICATION CODE. 26D10, 42A38.

1. INTRODUCTION.

Let \hat{f} be the Fourier transform of f defined by

 $\hat{f}(x) = \int e^{-2\pi i x y} f(y) dy, \quad x \in \mathbb{R}.$

If $f \in L^2(\mathbb{R})$ with L^2 -norm $||f||_2 = 1$, then by Plancherel's theorem $||\hat{f}||_2 = 1$, so that $|f(x)|^2$ and $|\hat{f}(y)|^2$ are probability trequency functions. The variance of a probability frequency function g is defined by

 $V[g] = \int_{\mathbb{R}} (x-m)^2 g(x) dx$ where $m = \int_{\mathbb{R}} xg(x) dx$

is the mean. With these notations, the Heisenberg uncertainty principle of quantum mechanics can be stated in terms of the Fourier transform by the inequality $V[|f|^2]V[|\hat{f}|^2] > (16\pi^2)^{-1}$.

In the sequel, we assume without loss of generality that the mean m = 0. If g is a probability frequency function, then the entropy of g is defined by

 $E[g] = \int_{D} g(x) \log g(x) dx.$

With f as above, Hirschman [1] proved that

$$E[|f|^{2}] + E[|\hat{f}|^{2}] \le E_{H}$$
(1.2)

with $E_{H} = 0$, and suggested that (1.2) holds with $E_{H} = \log 2-1$. If E_{H} has that form, then by an inequality of Shannon and Weaver [2] it follows that (1.2) implies (1.1). Using the Babenko-Beckner optimal form of the Hausdorff-Young inequality ([3])

$$||\hat{f}||_{p'} \leq A(p)||f||_{p}, 1 (1.3)$$

(1.1)

in Hirschman's proof of (1.2), then as Beckner [3] noted, (1.2) holds with $E_{H} = \log 2-1$.

A modest extension of (1.1) is obtained as follows: Let f on \mathbb{R} be differentiable, such that f(0) = 0. Then Hölder's and Hardy's inequality [4, Theorem 3.27] yield with 1

$$\int_{0}^{\infty} |f(x)|^{2} dx \leq (\int_{0}^{\infty} |x |f(x)|^{p} dx)^{1/p} (\int_{0}^{\infty} |f(x)/x|^{p'} dx)^{1/p'}$$

$$\leq p(\int_{0}^{\infty} |x |f(x)|^{p} dx)^{1/p} (\int_{0}^{\infty} |f'(x)|^{p'} dx)^{1/p'}.$$

Applying this estimate also to f(-x), then

$$\begin{split} ||f||_{2}^{2} &= \int_{0}^{\infty} |f(x)|^{2} dx + \int_{0}^{\infty} |f(-x)|^{2} dx \\ &\leq p[(\int_{0}^{\infty} |x |f(x)|^{p} dx)^{1/p} (\int_{0}^{\infty} |f'(x)|^{p'} dx)^{1/p'} \\ &+ (\int_{0}^{\infty} |x |f(-x)|^{p} dx)^{1/p} (\int_{0}^{\infty} |f'(-x)|^{p'} dx)^{1/p'}] \\ &\leq p(\int_{\infty}^{\infty} |x |f(x)|^{p} dx)^{1/p} (\int_{\infty}^{\infty} |f'(x)|^{p'} dx)^{1/p'}, \end{split}$$

where the last inequality follows from Hölder's inequality. Now by (1.3) and the fact that $\hat{f}'(y) = 2\pi i y \hat{f}(y)$ we obtain

THEOREM 1.1. If $f \in S(\mathbb{R})$ and f(0) = 0, then for 1

 $||f||_{2}^{2} \leq 2\pi p A(p) ||xf||_{p} ||y\hat{f}||_{p}.$ (1.4)

Note that the constant in (1.4) is slightly better than that in [4,\$1.4] but unlikely best possible.

The purpose of this paper is to give extensions of the Heisenberg-Weyl inequality (1.1). In the next section a new proof of the entropy inequality (1.2) for functions on \mathbb{R}^n is given and an n-dimensional Heisenberg-Weyl inequality is deduced. The n-dimensional generalization of inequality (1.4) is also given in the next section. The two inequalities are quite different, even in the case p = 2, but depend strongly on the sharp Hausdorff-Young inequality. In the third section a weighted form of the Heisenberg-Weyl inequality in one dimension is obtained from a weighted form of the Hausdorff-Young inequality ([5][6][7][8]). Unlike the constant A(p) in (1.3) the constant of the weighted Hausdorff-Young inequality (3.3) of (Theorem 3.1) is far from sharp. If the constant is not too large, then a weighted form of Hirschman's entropy inequality can also be given, from which another uncertainty inequality is deduced.

Throughout, p' = p/(p-1), with p' = ∞ if p = 1, is the conjugate index of p, and similarly for other letters. S(\mathbb{R}^n) is the Schwartz class of slowly increasing functions on \mathbb{R}^n . We say g is in the weighted L_w^r -space with weight w, if wg εL^r and norm $||g||_{r,w} = ||wg||_r$. If x $\varepsilon \mathbb{R}^n$, then x = (x_1, x_2, \dots, x_n) and dx = dx₁...dx_n the ndimensional Lebesgue measure. $f_i(x)$, x $\varepsilon \mathbb{R}^n$ denotes the partial derivative of f with respect to the ith component and $f_{ij} = (f_i)_j$. The letter C denotes a constant which may be different at different occurrences, but is independent of f.

2. THE HIRSCHMAN INEQUALITY.

The Fourier transform of f on \mathbb{R}^n is given by $\hat{f}(x) = \int_{-\infty} e^{-2\pi i x \cdot y} f(y) dy$

$$\mathbb{R}^{n} = \int_{\mathbb{R}^{n}} e^{-x_{1} - y_{1}} f(y) dy, \quad x \in \mathbb{R}^{n}, \quad x \cdot y = x_{1} y_{1} + \ldots + x_{n} y_{n};$$

and the entropy of a function on \mathbb{R}^n is defined as before with \mathbb{R} replaced by \mathbb{R}^n . We shall need the following well known result (c.f. [9; §13.32 ii]):

If
$$\int d\mu = 1$$
, then
X

$$\lim_{p \to 0^+} (\int |f|^p d\mu)^{1/p} = \exp \int \log |f| d\mu.$$
(2.1)

Using this fact we obtain easily the n-dimensional form of Hirschman's inequality (1.2)

THEOREM 2.1. If
$$f \in L^2(\mathbb{R}^n)$$
 such that $||f||_2 = ||\hat{f}||_2 = 1$, then

$$E[|f|^{2}] + E[|\hat{f}|^{2}] \leq n[\log 2 - 1], \qquad (2.2)$$

whenever the left side has meaning.

PROOF. Let $f \in (L^1 \cap L^2)(\mathbb{R}^n)$, then $f \in L^p(\mathbb{R}^n)$, $1 , and by the n-dimensional form of the sharp Hausdorff-Young inequality [3] (that is,(1.3) with A(p) replaced by <math>[A(p)]^n$) we obtain with p = 2-r, r > 0 and p' = 2-r', r' < 0

$$\left(\int_{\mathbb{R}^{n}} |\hat{f}(y)|^{2-r'} dy\right)^{-1/r'} \leq \left[\frac{(2-r)^{1/2r}}{(2-r')^{-1/(2r')}}\right]^{n} \left(\int_{\mathbb{R}^{n}} |f(x)|^{2-r} dx\right)^{1/r}.$$

Now let $d\hat{\mu} = |\hat{f}(y)|^2 dy$ and $d\mu = |f(x)|^2 dx$, then $\int_{\mathbb{R}^n} d\hat{\mu} = \int_{\mathbb{R}^n} d\mu = 1$, so that the inequality becomes

$$\left(\int_{\mathbb{R}^n} |\hat{f}(y)|^{-r'} d\hat{\mu} \right)^{-1/r'} / \left(\int_{\mathbb{R}^n} (1/|f(x)|)^r d\mu \right)^{1/r} \leq \left[(2-r)^{-1/(2r)} / (2-r')^{-1/(2r')} \right]^n.$$

But as $r \rightarrow o+$, $-r' \rightarrow o+$, so that by (2.1)

$$\exp(\int_{\mathbb{R}^{n}} \log |\hat{f}(y)| d\hat{\mu}) / \exp(\int_{\mathbb{R}^{n}} \log(|f(x)|^{-1}) d\mu)$$

$$= \exp(\int_{\mathbb{R}^{n}} |\hat{f}(y)|^{2} \log |\hat{f}(y)| dy + \int_{\mathbb{R}^{n}} |f(x)|^{2} \log |f(x)| dx) \leq \underbrace{\lim_{r \to 0}}_{r \to 0} \frac{(2-r)^{n}}{(2-r')^{-n}/(2r')}$$

$$= 2^{n/2} e^{-n/2}.$$

Taking logarithms on both sides we get

$$\int_{\mathbb{R}^n} |\hat{f}(y)|^2 \log |\hat{f}(y)| dy + \int_{\mathbb{R}^n} |f(x)|^2 \log |f(x)| dx \leq \frac{n}{2} [\log 2-1]$$

and this implies (2.2) in the case f ϵ (L $^1 \bigcap$ L $^2)(\mathbb{R}^n).$

If $f \in L^2$ the result is obtained as in [1] only now one takes for ω_T , $\omega_{\varepsilon}(x) = e^{-\pi \varepsilon |x|^2}$ and for Ω_T , $\hat{\omega}_{\varepsilon}(y) = \varepsilon^{-n/2} e^{-\pi |y|^2} / \varepsilon$. We omit the details.

If $|g| \in L^2(\mathbb{R})$ is a probability frequency function, then the relation between entropy and variance is expressed by $E[|g|^2] \ge -\frac{1}{2} - \frac{1}{2} \log(2\pi V[|g|^2])([2; p. 55-56])$. The n-dimensional form of this inequality is given in the following lemma:

LEMMA 2.1. ([2; p. 56-57]). Let $g \in L^2(\mathbb{R}^n)$ with $||g||_2 = 1$. If $B = (b_{ij})$ is the matrix with entries

$$b_{ij} = V[|g|^2] = \int_{\mathbb{R}^n} x_i x_j |g(x)|^2 dx, \quad i,j = 1,2,...,n;$$

then

$$E[|g|^2] \ge \frac{n}{2} \log (2\pi |b_{ij}|^{1/n}) - n/2$$
 where $|b_{ij}| = \det B$.

Using the lemma and Theorem 2.1, we easily establish an n-dimensional extension of the Heisenberg-Weyl inequality.

THEOREM 2.2. Let $f \in L^2(\mathbb{R}^n)$ with $||f||_2 = ||\hat{f}||_2 = 1$ and

$$b_{ij} = \int_{\mathbb{R}^n} x_i x_j |f(x)|^2 dx, \qquad \hat{b}_{ij} = \int_{\mathbb{R}} y_i y_j |\hat{f}(y)|^2 dy,$$

i,j = 1,2,...n; be the entries of the matrices B and \hat{B} respectively, then (det B)(det \hat{B}) \geq (16 π^2)⁻ⁿ. PROOF. By (2.2) and Lemma 2.1, n[log 2-1] \geq E[|f|²] + E[| \hat{f} |²] $\geq -\frac{n}{2} \log(2\pi |b_{ij}|^{1/n}) - \frac{n}{2} \log(2\pi |\hat{b}_{ij}|^{1/n}) - n,$

so that

$$\log 2 \ge -\frac{1}{2} \log(4\pi^2 |b_{ij}|^{1/n} |\hat{b}_{ij}|^{1/n}).$$

But then

4 > 1/[(det B)^{1/n}(det \hat{B})^{1/n}4 π^2],

which implies the result.

Clearly, if n = 1 we obtain at once (1.1). If n = 2 then

$$B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} = \begin{cases} \int_{\mathbb{R}^2} x_1^2 |f|^2 dx, & \int_{\mathbb{R}^2} x_1 x_2 |f|^2 dx \\ \int_{\mathbb{R}^2} x_2 x_1 |f|^2 dx, & \int_{\mathbb{R}^2} x_2^2 |f|^2 dx \end{cases},$$

with a similar expression for \hat{B} . Applying Theorem 2.2 we obtain

$$(\det B)(\det \hat{B}) = [(\int_{\mathbb{R}^2} x_1^2 |f|^2 dx)(\int_{\mathbb{R}^2} x_2^2 |f|^2 dx) - (\int_{\mathbb{R}^2} x_1 x_2 |f|^2 dx)^2]$$

$$\cdot [(\int_{\mathbb{R}^2} y_1^2 |\hat{f}|^2 dy) - (\int_{\mathbb{R}^2} y_1 y_2 |\hat{f}|^2 dy)^2] \ge (16 \pi^2)^{-2}.$$

If we denote the bracketed terms above by $D[|f|^2]$ and $D[|\hat{f}|^2]$, the discrepancy of Schwarz's inequality, or the difference between variance and covariance of $|f|^2$ and $|\hat{f}|^2$, then the two dimensional Heisenberg-Weyl inequality shows that the discrepancies of $|\hat{f}|^2$ and $|\hat{f}|^2$ cannot both be small; $D[|f|^2] D[|\hat{f}|^2] > (16 \pi^2)^{-2}$.

A different generalization of (1.1) may be obtained along the lines of Theorem 1.1. THEOREM 2.3. Let $f \in S(\mathbb{R}^n)$, such that $f(x_1, x_2, \dots, x_n) = 0$, whenever $x_i = 0$ for some i. If 1 and <math>A(p) is the constant of (1.3), then

$$||f||_{2}^{2} \leq [2\pi p A(p)]^{n} ||x_{1}...x_{n}f||_{p} ||y_{1}...y_{n}\hat{f}||_{p}.$$

PROOF. We only give the proof for n = 2 since the general case follows in exactly the same way. Let $f_{21}(x,y) = g(x,y)$, then

$$f(x,y) = \int_{0}^{x} \int_{0}^{y} g(s,t) dt ds$$

and by Hölder's and the two dimensional Hardy inequality, with $\mathbb{R}^2_+ = (0,\infty) \times (0,\infty)$,

$$\int_{\mathbb{R}^{2}_{+}} |f(x,y)|^{2} dx dy \leq (\int_{\mathbb{R}^{2}_{+}} |xy | f(x,y)|^{p} dx dy)^{1/p} (\int_{\mathbb{R}^{2}_{+}} |f(x,y)/xy|^{p'} dx dy)^{1/p'}$$

$$\leq p^{2} (\int_{\mathbb{R}^{2}_{+}} |xy | f(x,y)|^{p} dx dy)^{1/p} (\int_{\mathbb{R}^{2}_{+}} |f_{21}(x,y)|^{p'} dx dy)^{1/p'} .$$

On applying this estimate four times we obtain with $d\mu$ = dxdy

$$||f||_{2}^{2} = \int_{\mathbb{R}^{2}_{+}} (|f(x,y)|^{2} + |f(x,-y)|^{2} + |f(-x,-y)|^{2} + |f(-x,y)|^{2}) d\mu$$

$$\leq p^{2} \{ (\int_{\mathbb{R}^{2}_{+}} |xy f(x,y)|^{p} d\mu)^{1/p} (\int_{\mathbb{R}^{2}_{+}} |f_{21}(x,y)|^{p'} d\mu)^{1/p'} \\ + (\int_{\mathbb{R}^{2}_{+}} |xy f(x,-y)|^{p} d\mu)^{1/p} (\int_{\mathbb{R}^{2}_{+}} |f_{21}(x,-y)|^{p'} d\mu)^{1/p'} \\ + (\int_{\mathbb{R}^{2}_{+}} |xy f(-x,-y)|^{p} d\mu)^{1/p} (\int_{\mathbb{R}^{2}_{+}} |f_{21}(-x,-y)|^{p'} d\mu)^{1/p'} \\ + (\int_{\mathbb{R}^{2}_{+}} |xy f(-x,y)|^{p} d\mu)^{1/p} (\int_{\mathbb{R}^{2}_{+}} |f_{21}(-x,y)|^{p'} d\mu)^{1/p'} \} \\ \leq p^{2} \{ (\int_{\mathbb{R}^{2}_{+}} |xy|^{p} [|f(x,y)|^{p} + |f(x,-y)|^{p} + |f(-x,-y)|^{p} + |f(-x,y)|^{p}] d\mu)^{1/p} \} \\ \times (\int_{\mathbb{R}^{2}_{+}} |f_{21}(x,y)|^{p'} + |f_{21}(x,-y)|^{p'} \\ + |f_{21}(-x,-y)|^{p'} + |f_{21}(-x,y)|^{p'}] d\mu)^{1/p'} \} \\ = p^{2} (\int_{\mathbb{R}^{2}_{+}} |xy f(x,y)|^{p} d\mu)^{1/p} (\int_{\mathbb{R}^{2}_{+}} |f_{21}(x,y)|^{p'} d\mu)^{1/p'}, \end{aligned}$$

where the last inequality follows from Hölder's inequality. But by the sharp form of the Hausdorff-Young inequality with n = 2 we obtain $||f||_2^2 \leq [p A(p)]^2 ||xyf||_p ||\hat{f}_{21}||_p$. Since $(\hat{f}_{21})(s,t) = 4\pi^2 st \hat{f}(s,t)$ the result follows.

3. WEIGHTED HIRSCHMAN ENTROPY INEQUALITY AND WEIGHTED HEISENBERG-WEYL INEQUALITY.

The results of the last section show that the Heisenberg-Weyl inequality is a consequence of the Hausdorff-Young theorem. Recently a number of weighted Hausdorff-Young inequalities have been obtained [5], [6], [7] and [8]. We shall use these results in this section to obtain a weighted Hirschman entropy inequality as well as weighted form of the Heisenberg-Weyl inequality. Here we consider weighted extensions in \mathbb{R}^1 only.

Recall that if g is a Lebesgue measurable function on \mathbb{R} , then the equi-measurable decreasing rearrangement of g is defined by $g^{*}(t) = \inf\{y > 0: |\{x \in \mathbb{R}: |g(x)| > y\}| \leq t\}$, where y > 0 and |E| denotes Lebesgue measure of the set E. Clearly, if g is an even function on \mathbb{R} , decreasing on $(0,\infty)$, then for t > 0, $g^{*}(t) = g(t/2)$. We shall use this fact below.

DEFINITION 3.1. Let u and v be locally integrable functions of R. We write $(u,v) \in F_{p,q}^*$, $1 \le p \le q \le \infty$, if

$$\sup_{0} \left(\int_{0}^{s} [u^{*}(t)]^{q} dt\right)^{1/q} \left(\int_{0}^{1/s} [(1/v)^{*}(t)]^{p'} dt\right)^{1/p'} < \infty,$$
(3.1)

where in the case p = 1 the second integral is replaced by the essential supremum of $(1/v)^{*}(t)$ over (0, 1/s).

If u and 1/v are even and decreasing on
$$(0, \infty)$$
 then (3.1) is equivalent to

$$\sup_{s>o} (\int_{0}^{s/2} [u(x)]^{q} dx)^{1/q} (\int_{0}^{1/(2s)} v(x)^{-p'} dx)^{1/p'} < \infty$$
(3.2)

and in this case we write (u, v) $\varepsilon F_{p,q}$.

The weighted Hausdorff-Young inequality is given in the following theorem:

THEOREM 3.1. ([5; Theorem 1.1]). Suppose (u,v) $\varepsilon F_{p,q}^*$, $1 \le p \le q \le \infty$ and $f \varepsilon L_v^p$. (i) If $\lim_{n \to \infty} ||f_n - f||_{p,v} = 0$ for a sequence of simple functions, then $\{\hat{f}_n\}$ con-

verges in L_u^q to a function $\hat{f} \in L_u^q$. \hat{f} is independent of the sequence $\{\hat{f}_n\}$ and is called

the Fourier transform of f.

(ii) there is a constant B > 0 such that for all
$$f \in L_v^p$$

 $||\hat{f}||_{q,u} < B||f_{p,v}.$ (3.3)
(iii) If $g \in L_{1/u}^q$, $q > 1$, then Parseval's formula
 $\int_{\mathbb{R}} \hat{f}(y)g(y)dy = \int_{\mathbb{R}} f(t)\hat{g}(t)dt$

holds.

We note ([5], [6], [8]) that Theorem 3.1 is sharp in the sense that if u and v are even and satisfy (3.3), then (u, v) satisfies (3.2). The constant B in (3.3) is not sharp, however it is of the form B = k.C where k = k(p,q) is independent of u and v and C is the supremum of (3.1), and in the case u, 1/v decreasing and even the supremum (3.2).

A special case of Theorem 3.1 is the following: COROLLARY 3.1. Suppose $f \in L_v^{p_1/2/p}$, $(u^{1-2/p'}, v^{1-2/p}) \in F_{p,p'}^*$, 1 , whereu and v are even, decreasing as $(0,\infty)$ then

$$\binom{\int u(y)^{p'-2} |\hat{f}(y)|^{p'}}{\mathbb{R}} < k.C_{p} \binom{\int v(x)^{p-2} |f(x)|}{\mathbb{R}} \frac{p_{dx}}{p_{dx}}^{1/p}$$

$$C_{p} = \sup_{s \geq 0} \binom{\int s/2}{0} u(x)^{p'-2} dx \frac{1/p'}{0} \binom{\int 1/(2s)}{0} v(x)^{(2-p)p'/p} dx \frac{1/p'}{p}.$$

$$(3.4)$$

where

Utilizing the last result we now give a weighted form of Hirschman's entropy inequality.

PROPOSITION 3.1. Suppose f $\in L^2 \cap L^1_{1/v}$, where u and v satisfy the conditions of Corollary 3.1. If $||f||_2 = 1$ and (3.4) holds with 0 < k ≤ 2 and C_p remains bounded as $p \rightarrow 2$, then

$$\int_{\mathbb{R}} |\hat{f}(y)|^{2} \log |u(y)\hat{f}(y)|^{2} dy + \int_{\mathbb{R}} |f(x)|^{2} \log |v(x)f(x)|^{2} dx$$

 $\le 2 \log k + 8 \sup_{s>0} (\int_{0}^{s/2} \int_{0}^{1/(2s)} \log |u(x)v(y)| dxdy).$ PROOF. Since $f \in L_{v}^{p} 1-2/p$, 1 , we apply Corollary 3.1 with <math>p = 2-r, r > 0, p' = 2-r', r' < 0 and $d\hat{u}(y) = |\hat{f}(y)|^{2} dy$, $d\mu(x) = |f(x)|^{2} dx$. Then (3.4) has the form $(\int_{\mathbb{R}} |u(y)\hat{f}(y)|^{-r'} d\mu)^{1/(2-r')} \leq k \sup_{s>0} (\int_{0}^{s/2} |u(x)^{-r'} dx|^{1/(2s)} v(x)^{-r'} dx]^{1/(2-r')}$

•
$$(\int |v(x)f(x)|^{-r}d\mu)^{1/(2-r)}$$

or, on raising the inequality of the power (2-r')(-1/r'), equivalently $\frac{(\int_{\mathbb{R}} |u(y)\hat{f}(y)|^{-r'})^{-1/r'}}{(\int_{\mathbb{R}} |v(x)f(x)|^{-r}d\mu)^{1/r}} \leq k(\frac{k}{2})^{-2/r'}M_{r'},$

where

$$M_{r} = \sup_{s>0} \left[\int_{0}^{s/2} \int_{0}^{1/(2s)} [u(x)v(y)]^{-r'} 4dxdy]^{-1/r'} \right].$$

Given $\varepsilon > 0$ there is an s₀ > 0 such that

$$M_{\mathbf{r}} \leq \left[\int_{0}^{s_{0}/2} \int_{1}^{1/(2s)} \left[u(\mathbf{x})v(\mathbf{y})\right]^{-\mathbf{r}'} \mathbf{r} d\mathbf{x} d\mathbf{y}\right]^{-1/\mathbf{r}'} + \varepsilon$$

so that

$$\begin{cases} \int_{\mathbb{R}} |u(y)\hat{f}(y)|^{-r'}d_{\mu}^{-1/r'} / \int_{\mathbb{R}} |v(x)f(x)|^{-r}d_{\mu}^{-1/r'} \\ \leq k([\int_{\mathbb{R}}^{s_{0}/2}\int_{0}^{1/(2s_{0})}[u(x)v(y)]^{-r'}4dxdy]^{-1/r'} + \varepsilon), \qquad (3.5) \end{cases}$$

where we used the fact that $k/2 \leq 1$. Now as $r \neq 0+$, $r' \neq 0-$, then on applying (2.1) to both sides of (3.5) we obtain

$$\begin{split} \exp(\int_{\mathbb{R}} \log |u(y)\hat{f}(y)|d\hat{\mu})/\exp(\int_{\mathbb{R}} \log |1/[v(x)f(x)]|d\mu) \\ &\leqslant k[\exp \int_{0}^{s} o^{/2} \int_{0}^{1/(2s_{0})} \log[v(y)u(x)] 4 dx dy + \varepsilon] \\ &\leqslant k[\exp \sup_{s>o} \int_{0}^{s/2} \int_{0}^{1/(2s)} \log[u(x)v(y)] 4 dx dy + \varepsilon]. \end{split}$$

But ϵ > 0 is arbitrary so that on taking logarithms we have

$$\frac{1}{2} \int_{-\infty}^{\infty} |\hat{f}(y)|^2 \log |u(y)\hat{f}(y)|^2 dy + \frac{1}{2} \int_{-\infty}^{\infty} |f(x)|^2 \log |v(x)f(x)|^2 dx$$

$$\leq \log k + 4 \sup_{s>0} (\int_{0}^{s/2} \log u(x) dx + \int_{0}^{1/(2s)} \log v(y) dy)$$

which yields the result.

Note that if $u = v \equiv 1$ and if $k \leq \sqrt{2/e}$ we obtain (2.2) with n = 1. We can write the conclusion of Proposition 3.1 in the form

$$E[|f|^{2}] + E[|\hat{f}|^{2}] \leq 2 \log k + 8 \sup_{s>0} (\int_{0}^{s/2} \int_{0}^{1/(2s)} \log|u(x)v(y)| dxdy) - \int_{\mathbb{R}} |\hat{f}(y)|^{2} \log|u(y)|^{2} dy - \int_{\mathbb{R}} |f(x)|^{2} \log|v(x)|^{2} dx.$$

But since ([2]) $E[|f|^2] \ge -\frac{1}{2} - \frac{1}{2} \log(2\pi V[|f|^2])$ and also with f replaced by \hat{f} we obtain another uncertainty inequality

$$V[|f|^{2}] V[|\hat{f}|^{2}] \ge \frac{k^{-4}}{4\pi^{2}e^{2}} \exp[-16 \sup_{s>0} \int_{0}^{s/2} \int_{0}^{1/(2s)} \log|uv| dxdy]$$
$$x \exp(2 \int_{\mathbb{D}} |\hat{f}|^{2} \log|u|^{2} dy) \exp(2 \int_{\mathbb{D}} |f|^{2} \log|v|^{2} dx)$$

If $u = v \equiv 1$ and $k = \sqrt{2/e}$ in this estimate we obtain (1.1).

THEOREM 3.2. (Heisenberg-Weyl inequality). If (1/u, v) ϵ F $_{p,q}^{\star}$, l \leqslant p \leqslant q < ∞ and f ϵ S(R), then

$$||f||_{2}^{2} \leq C(\int_{|R|} |u(x)xf(x)|^{q'} dx)^{1/q'} (\int_{\mathbb{R}} |v(y)y\hat{f}(y)|^{p} dy)^{1/p}.$$
(3.6)

PROOF. Integration by parts and Hölder's inequality show that for $1 \le q \le \infty$ $||f||_2^2 \le 2 \int_{\mathbb{D}} |x||f(x)||f'(x)| dx$

$$\leq 2 (\int_{\mathbb{R}} |xu(x)f(x)|^{q'} dx)^{1/q'} (\int_{\mathbb{R}} |f'(x)/u(x)|^{q} dx)^{1/q}$$

$$\leq 2 C (\int_{\mathbb{R}} |xu(x)f(x)|^{q'} dx)^{1/q'} (\int_{\mathbb{R}} |v(y)\hat{f}'(y)|^{p} dx)^{1/p},$$

where the last inequality follows from (3.3). Since $\hat{f}'(y) = 2\pi i y \hat{f}(y)$ the result follows.

Note that the case p = 1 also holds, provided the second integral in the $F_{p,q}^{*}$ condition is interpreted as the essential supremum of $(1/v)^{*}$ over (0, 1/s).

The same result holds also if we take $(1/u, v) \in F_{p,q}$.

Observe also that the case $u = v \equiv 1$ and q = p', 1 reduces to (1.4), but with a different constant.

Weighted inequalities of the form (3.6) were also obtained by Cowling and Price [3] but by quite different methods.

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Lean Yu, Academy of Mathematics and Systems Science, Chinese Academy of Sciences, Beijing 100190, China; Department of Management Sciences, City University of Hong Kong, Tat Chee Avenue, Kowloon, Hong Kong; yulean@amss.ac.cn

Shouyang Wang, Academy of Mathematics and Systems Science, Chinese Academy of Sciences, Beijing 100190, China; sywang@amss.ac.cn

K. K. Lai, Department of Management Sciences, City University of Hong Kong, Tat Chee Avenue, Kowloon, Hong Kong; mskklai@cityu.edu.hk

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