

## POINT REGULARITY OF $p$ -STABLE DENSITY IN $\mathcal{R}^d$ AND FISHER INFORMATION

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*Abstract.* In the paper we prove that the  $n$ -th directional derivative of a  $p$ -stable density  $f(x)$  in the direction  $a$  can be estimated by

$$|D_a^n f(x)| \leq \frac{C(u)}{1+|x|} [f(x)]^{(1-u)[p/(1+p)]},$$

where  $0 < u < 1$ , and  $C$  depends also on geometrical properties of the Lévy measure. This inequality helps us to calculate the Fisher information of stable measures.

**Introduction.** In this paper,  $|\cdot|$  denotes Euclidean norm and  $\langle \cdot, \cdot \rangle$  is a scalar product in  $\mathcal{R}^d$ . We say that  $f(y)$  is a *density of a  $p$ -stable vector* in  $\mathcal{R}^d$  ( $0 < p < 2$ ) if the Fourier transform of  $f(x)$  is of the form

$$\int_{\mathcal{R}^d} e^{i\langle x, y \rangle} f(y) dy = \exp\left(- \int_{S^{d-1}} |\langle x, s \rangle|^p \sigma(ds)\right)$$

for a certain symmetric Borel measure  $\sigma$ . Moreover,  $\sigma$  is finite, positive, concentrated on  $S^{d-1}$  and  $\text{lin}(\text{supp } \sigma) = \mathcal{R}^d$ . The measure  $\sigma$  (called *spectral*) is unique. Let us write

$$|x|_\sigma^p = \int_{S^{d-1}} |\langle x, s \rangle|^p \sigma(ds), \quad \tau(\sigma) = \inf_{|x|=1} |x|_\sigma^p.$$

Notice that if  $\tau(\sigma) > 0$ , then the Fourier transform of  $f(x)$  can be approximated by  $\exp(-\tau(\sigma)|x|^p)$ , so that  $f(x) \in C^\infty$ .

It was proved in Głowacki [3] that

$$|D_{e_i}^n f(x)| \leq \frac{C}{1+|x|^{n+p}}$$

for some constant  $C$ . Unfortunately, this result does not allow us to answer the question how to estimate the derivatives using the density. Inspiration for this question comes from the theory of admissible translates (Kakutani Theorem)

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for products of measures. In order to answer the question whether  $\underline{a} = (a_1, a_2, \dots)$  is an admissible translate of  $\underline{\mu} = (f_1 dx) \times (f_2 dx) \times \dots$ , where  $f_i$  are densities on  $\mathcal{R}^d$ , one has to check if

$$\sum a_i^2 \int \frac{|Vf|^2}{f_i} dx < \infty.$$

Our main result allows us to characterize admissible translates of infinite product of 2-dimensional stable measures; this situation occurs in the case of harmonizable  $p$ -stable process.

**Preliminaries.** For the rest of the paper,  $\sigma$  will denote the spectral measure of  $p$ -stable measure  $\mu(dx) = f(x) dx$ . We will consider only finite positive Borel measures  $\sigma$ .

For  $\tau(\sigma)$  we list some simple facts.

**FACT 1.** Let  $M$  be the set of all symmetric probability measures concentrated on  $S^{d-1}$ . The function  $\tau(\sigma): M \rightarrow \mathcal{R}$  is continuous in the weak topology.

**Proof.** If  $\sigma$  is fixed, the function  $x \rightarrow \int_{S^{d-1}} |\langle x, s \rangle|^p \sigma(ds)$  is continuous; hence there exists  $x(\sigma) \in S^{d-1}$  such that

$$\tau(\sigma) = \int |\langle x(\sigma), s \rangle|^p \sigma(ds) = \int_{S^{d-1} \times S^{d-1}} |\langle y, s \rangle|^p d(\delta_{x(\sigma)} \times \sigma)(y, s),$$

and we have

$$\tau(\sigma) \leq \int |x|^p |s|^p \sigma(ds) = \sigma(S^{d-1}) = 1,$$

where  $\delta_{x(\sigma)}$  denotes the unit measure concentrated at the point  $x(\sigma)$ .

Let  $\sigma_n \xrightarrow{w} \sigma_0$  ( $w$  means "weakly") and  $\tau_0 = \lim_{k \rightarrow \infty} \tau(\sigma_{n_k})$  for a subsequence  $n_k$ . We can also assume that  $\lim_{k \rightarrow \infty} x(\sigma_{n_k}) = x_0$  for any  $x_0 \in S^{d-1}$ . Thus

$$\delta_{x(\sigma_{n_k})} \times \sigma_{n_k} \xrightarrow{w} \delta_{x_0} \times \sigma_0 \quad \text{and} \quad \int |\langle y, s \rangle|^p d(\delta_{x(\sigma_{n_k})} \times \sigma_{n_k}) \leq \int |\langle x, s \rangle|^p \sigma_{n_k}(ds)$$

for every  $x \in S^{d-1}$ . By the inequality

$$\lim_{k \rightarrow \infty} \int |\langle y, s \rangle|^p d(\delta_{x(\sigma_{n_k})} \times \sigma_{n_k}) = \int |\langle x_0, s \rangle|^p \sigma_0(ds) \leq \int |\langle x, s \rangle|^p \sigma_0(ds),$$

we set  $\tau(\sigma_0) = \lim \tau(\sigma_{n_k})$ , which completes the proof.

The next result is needed only for technical reasons.

**FACT 2.** Let  $Z_1, Z_2, \dots, Z_d$  denote independent random variables with identical distributions equal to  $\sigma$  ( $\sigma$  is the normalized spectral measure). Then:

$$\tau(\sigma) > 0 \Leftrightarrow \exists 0 < q \leq 1 \quad \exists \alpha > 0 \quad P(|\det(Z_1, \dots, Z_d)| > \alpha) = q.$$

**Proof.** ( $\Leftarrow$ ) If  $\tau(\sigma) = 0$ , then there exists  $x_0 \in S^{d-1}$  such that

$$\int |\langle x_0, s \rangle|^p \sigma(ds) = 0,$$

so that  $\text{supp } \sigma \subset \{x_0\}^\perp$ . Then  $P(Z_1 \in \{x_0\}^\perp, \dots, Z_d \in \{x_0\}^\perp) = 1$ , and hence  $P(\det(Z_1, \dots, Z_d) = 0) = 1$ , a contradiction.

( $\Rightarrow$ ) Let  $\tau(\sigma) > 0$ . We will find  $x_1, x_2, \dots, x_d$  such that  $x_i \in \text{supp } \sigma$  and  $x_1, x_2, \dots, x_d$  are linearly independent. Recall that

$$\text{supp } \sigma = \{x: \forall \varepsilon > 0, \sigma(B(x, \varepsilon)) > 0\},$$

where  $B(x, \varepsilon)$  is a ball with center  $x$  and radius  $\varepsilon$ .

Take arbitrary  $x_1 \in \text{supp } \sigma$ ,  $x_1 \neq 0$ . Next take  $w \in S^{d-1}$  such that  $\langle w, x_1 \rangle = 0$ . Since also  $\int |\langle w, s \rangle|^p \sigma(ds) > 0$ , there exists  $x_2 \in \text{supp } \sigma - \text{lin } \{x_1\}$ , so we have found  $x_1$  and  $x_2$ .

If we have chosen  $x_1, x_2, \dots, x_r$ , then take  $w \in \text{lin } \{x_1, x_2, \dots, x_r\}^\perp$ ,  $w \in S^{d-1}$ . Since  $\int |\langle w, s \rangle|^p \sigma(ds) > 0$ , there exists

$$x_{r+1} \in \text{supp } \sigma - \text{lin } \{x_1, x_2, \dots, x_r\}$$

and we have found  $x_{r+1}$ . This process ends when we reach  $r = d$ . Of course,

$$(x_1, x_2, \dots, x_d) \in A = \{(y_1, y_2, \dots, y_d): \det [y_1, y_2, \dots, y_d] \neq 0\},$$

and  $A$  is open in  $(\mathcal{R}^d)^d$ , so there exist  $\varepsilon_1, \varepsilon_2, \dots, \varepsilon_d$  such that  $B(x_1, \varepsilon_1) \times \dots \times B(x_d, \varepsilon_d) \in A$ . Then

$$\begin{aligned} P(|\det(Z_1, \dots, Z_d)| > 0) &\geq P(Z_1 \in B(x_1, \varepsilon_1), \dots, Z_d \in B(x_d, \varepsilon_d)) \\ &= P(Z_1 \in B(x_1, \varepsilon_1)) \cdot \dots \cdot P(Z_d \in B(x_d, \varepsilon_d)) > 0. \end{aligned}$$

This completes the proof.

Now we present the main tool of our proof (see [5] and [6]). Assume that  $X_1, X_2, \dots$  are i.i.d.,  $P(X_i \geq x) = \exp(-x)$ ,  $x \geq 0$ ;  $\Gamma_n = X_1 + X_2 + \dots + X_n$ ;  $g_1, g_2, \dots$  are i.i.d.,  $g_i \sim N(0, 1)$ ;  $Z_1, Z_2, \dots$  are i.i.d.,  $Z_i \stackrel{d}{=} \sigma$ ; moreover,  $(X_i)$ ,  $(g_i)$ , and  $(Z_i)$  are mutually independent. In this case,  $\sum_{i=1}^\infty (\Gamma_i)^{-1/p} Z_i g_i$  converges a.s. and

$$(1) \quad P(\eta \in A) = E P(C_p \sum_{i=1}^\infty (\Gamma_i)^{-1/p} g_i Z_i \in A \mid \Gamma, Z),$$

where  $\eta(dx) = f(x) dx$  is a  $p$ -stable measure with spectral measure  $\sigma$  and

$$1/C_p = \int_0^\infty x^{-p} \sin x \, dx.$$

Since for fixed  $(\Gamma, Z)$  the series  $\sum_{i=1}^\infty (\Gamma_i)^{-1/p} Z_i g_i$  is a Gaussian vector, we will need some simple facts about Gaussian distributions.

A symmetric measure  $\mu$  is Gaussian (stable with parameter  $p = 2$ ) if

$$\int \exp(i \langle x^*, x \rangle) \mu(dx) = \exp(-\frac{1}{2} \int \langle x^*, x \rangle^2 \mu(dx)), \quad x^* \in \mathcal{R}^d.$$

The measure  $\mu$  generates quadratic form on  $\mathcal{R}^d$ : for  $\bar{x}, \bar{y} \in \mathcal{R}^d$

$$\langle \bar{x}, \bar{y} \rangle_1 = \int \langle \bar{x}, x \rangle \langle \bar{y}, x \rangle \mu(dx).$$

Then for a matrix  $A = [a_{ij}]_{d \times d}$  with entries  $a_{ij} = \langle e_i, e_j \rangle_1$ , we have

$$Ax = \sum_{i=1}^d v_i \langle x, v_i \rangle \lambda_i^2$$

for some orthonormal system  $\{v_1, \dots, v_d\}$  in  $\mathcal{R}^d$  and

$$\mu \stackrel{d}{=} v_1 g_1 \lambda_1 + \dots + v_d g_d \lambda_d,$$

where  $g_i$  are i.i.d., and  $g_i \sim N(0, 1)$ .

Observe that if

$$\mu \stackrel{d}{=} \sum_{i=1}^d g_i Z_i,$$

where  $Z_i$  are arbitrary vectors from  $\mathcal{R}^d$  with  $\text{lin}(Z_1, \dots, Z_d) = \mathcal{R}^d$ , then  $A = [Z] \cdot [Z]^T$ , where  $[Z]$  is a matrix with columns  $Z_1, Z_2, \dots, Z_d$ .

Let us put the eigenvalues in the following order:  $\lambda_1^2 \geq \lambda_2^2 \geq \dots \geq \lambda_d^2$ .

PROPOSITION 1 (see Bierezin [1]). *If*

$$\mu = \mathcal{L} \left( \sum_{i=1}^d v_i \lambda_i g_i \right) = \mathcal{L} \left( \sum_{i=1}^d Z_i g_i \right),$$

and  $g_i \sim N(0, 1)$ ,  $\{v_1, v_2, \dots, v_d\}$  is an orthonormal system,  $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_d > 0$ , then

$$(a) \quad \lambda_1^2 = \sup_{|x|=1} \int \langle x, n \rangle^2 \mu(dn);$$

$$(b) \quad \lambda_d^2 = \inf_{|x|=1} \int \langle x, n \rangle^2 \mu(dn);$$

$$(c) \quad \lambda_d^2 \geq (\det [Z])^2 \cdot \left( \frac{d-1}{\sum_{i=1}^d |Z_{ii}|^2} \right)^{d-1}.$$

Proof. (a) and (b). We have

$$\int \langle x, n \rangle^2 \mu(dn) = E \langle x, \sum v_i \lambda_i g_i \rangle^2 = \sum \langle x, v_i \rangle^2 \lambda_i^2.$$

Hence for  $|x| = 1$  we obtain  $\lambda_d^2 \leq \int \langle x, n \rangle^2 \mu(dn) \leq \lambda_1^2$ , but

$$\int \langle v_1, n \rangle^2 \mu(dn) = \lambda_1^2 \quad \text{and} \quad \int \langle v_d, n \rangle^2 \mu(dn) = \lambda_d^2.$$

(c) Let  $A = [Z] \cdot [Z]^T$ , the covariance matrix of  $\mu$ ,

$$A = \begin{bmatrix} \lambda_1^2 & & 0 \\ & \ddots & \\ 0 & & \lambda_d^2 \end{bmatrix}$$

in the basis  $\{v_1, \dots, v_d\}$ . Then  $\text{Tr} A = \lambda_1^2 + \dots + \lambda_d^2$  and, by the inequality between arithmetic and geometric means,

$$\frac{\text{Tr} A - \lambda_d^2}{d-1} = \frac{\lambda_1^2 + \dots + \lambda_{d-1}^2}{d-1} \geq d^{-1} \sqrt{\frac{\lambda_1^2 \cdot \dots \cdot \lambda_{d-1}^2}{\lambda_d^2}} = \frac{d^{-1} \sqrt{\det A}}{d^{-1} \sqrt{\lambda_d^2}}$$

Hence

$$\lambda_d^2 \geq (\det A) \cdot \left(\frac{d-1}{\text{Tr} A}\right)^{d-1}$$

and

$$\begin{aligned} \text{Tr} A &= \sum_{i=1}^d a_{ii} = \sum_{i=1}^d \mathbb{E} \langle e_i, \sum_j Z_j g_j \rangle^2 \\ &= \sum_{i=1}^d \left( \sum_j \langle e_i, Z_j \rangle^2 \right) = \sum_i \sum_j \langle e_i, Z_j \rangle^2 = \sum_i |Z_i|^2, \end{aligned}$$

which proves (c).

**The main result.** Now we can formulate our result.

**THEOREM 1.** *There exists a function  $C(\cdot, \cdot, \cdot): \mathcal{R}^3 \rightarrow \mathcal{R}_+$  such that, for every  $p$ -stable density  $f(x)$  on  $\mathcal{R}^d$  with spectral measure  $\sigma$ , we have*

$$\forall x \in \mathcal{R}^d \quad \forall 0 < \alpha < 1 \quad \forall a \in S^{d-1} \quad \forall n \in \mathbb{N}$$

$$|D_a^n f(x)| \leq \frac{C(\tau(\sigma), \alpha, n)}{1 + |x|} [f(x)]^{(1-\alpha)[p/(1+p)]},$$

where  $D_a^n$  denotes the  $n$ -th directional derivative in the direction  $a$ .

The idea of proof is to look at  $\mu$  as a mixture of Gaussian measures. Let

$$\mu = \mathbb{E} \mu_{(\Gamma, Z)}, \quad \text{where } \mu_{(\Gamma, Z)} \stackrel{d}{=} C_p \sum_{i=1}^{\infty} (\Gamma_i)^{-1/p} Z_i g_i$$

and  $(\Gamma, Z)$  are fixed. Let  $\lambda_d(\Gamma, Z) \leq \dots \leq \lambda_1(\Gamma, Z)$  be eigenvalues and  $(v_k(\Gamma, Z))_{k=1}^d$  be an orthonormal basis generated by  $\mu_{(\Gamma, Z)}$ .

For  $\lambda_1(\Gamma, Z)$  and  $\lambda_d(\Gamma, Z)$  we have two lemmas.

**LEMMA 1.**  $\mathbb{E} \lambda_1^{\beta}(\Gamma, Z) \leq C_p^2 \mathbb{E} (\sum_{i=1}^{\infty} \Gamma^{-2/p})^{\beta/2} < \infty$  for  $0 \leq \beta < p$ .

**Proof.** We have

$$X_{(\Gamma, Z)} = C_p \sum_{i=1}^{\infty} (\Gamma_i)^{-1/p} Z_i g_i$$

and, by Proposition 1 (a),

$$\lambda_1^2(\Gamma, Z) = \sup_{|x|=1} \mathbb{E} \langle x, X_{(\Gamma, Z)} \rangle^2 = C_p^2 \sup_{|x|=1} \sum_{i=1}^{\infty} (\Gamma_i)^{-2/p} \langle x, Z_i \rangle^2 \leq C_p^2 \sum_{i=1}^{\infty} (\Gamma_i)^{-2/p}.$$

A series  $\sum_{i=1}^{\infty} (\Gamma_i)^{-2/p}$  is a  $(p/2)$ -stable variable (Linde [6]), so it has moments less than  $p/2$ . This completes the proof.

LEMMA 2.  $E \lambda_d^{-\beta}(\Gamma, Z) < \infty$  for  $\beta \geq 0$ . Moreover,

$$E \lambda_d^{-\beta}(\Gamma, Z) \leq C_d \frac{1}{\alpha} w_{\beta}(1-q),$$

where

$$w_{\beta}(x) = 1 + \sum_{r=1}^{\infty} \left( d(r+1) + \frac{2\beta}{p} \right)^{(2\beta/p)+1} x^r$$

for  $\alpha$  and  $q$  as described in Fact 2.

Proof. We have

$$X_{(\Gamma, Z)} = C_p \sum (\Gamma_i)^{-1/p} g_i Z_i = \sum_{k=0}^{\infty} X_k(\Gamma, Z),$$

where

$$X_k(\Gamma, Z) = C_p \sum_{r=0}^{d-1} (\Gamma_{dk+r})^{-1/p} Z_{dk+r} g_{dk+r}.$$

Then

$$\lambda_d^2(\Gamma, Z) = \inf_{|x|=1} E_{(\Gamma, Z)} \langle x, X_{(\Gamma, Z)} \rangle^2 = \inf_{|x|=1} \sum_{k=0}^{\infty} \langle x, X_k \rangle^2 \geq \sum_{k=0}^{\infty} \lambda_{d,k}^2,$$

where

$$\begin{aligned} \lambda_{d,k}^2 &= \inf_{|x|=1} E_{(\Gamma, Z)} \langle x, X_k \rangle^2 = \inf_{|x|=1} C_p^2 \sum_{r=0}^{d-1} E_{(\Gamma, Z)} (\Gamma_{dk+r})^{-2/p} \langle x, Z_{dk+r} \rangle^2 \\ &\geq C_p^2 \inf_{|x|=1} E_{(\Gamma, Z)} \Gamma_{d(k+1)}^{-2/p} \left( \sum_{r=0}^{d-1} \langle x, Z_{dk+r} \rangle^2 \right) \\ &\geq C_p^2 \Gamma_{d(k+1)}^{-2/p} \cdot (\det [Z_{dk}, \dots, Z_{dk+d-1}])^2 \left( \frac{d-1}{d} \right)^{d-1}. \end{aligned}$$

In the above we have used Proposition 1 (c) and the fact that  $\Gamma_k$  is increasing.

Now we follow the paper of Pap [8]. Since  $\text{lin}(\text{supp } \sigma) = \mathcal{R}^d$ , by Fact 2 there exist  $\alpha > 0$  and  $0 < q \leq 1$  such that

$$P(|\det [Z_1, \dots, Z_d]|^2 > \alpha) = q.$$

Consequently,

$$E \lambda_d^{-2\beta} \leq C_d E \left[ \sum_{k=0}^{\infty} \Gamma_{d(k+1)}^{-2/p} \cdot (\det [Z_{dk}, \dots, Z_{dk+d-1}])^2 \right]^{-\beta}.$$

Let us put  $t = \inf_{k \geq 1} (\det [Z_{dk}, \dots, Z_{dk+d-1}])^2 \geq \alpha$ ; then

$$E \left[ \sum_{k=0}^{\infty} \Gamma_{d(k+1)}^{-2/p} (\det [Z_{dk}, \dots, Z_{dk+d-1}])^2 \right]^{-\beta}$$

$$\begin{aligned}
&= \sum_{r=1}^{\infty} \mathbb{E} \left[ \sum_{k=0}^{\infty} \Gamma_{d(k+1)}^{-2/p} (\det [Z_{dk}, \dots, Z_{dk+d-1}])^2 \right]^{-\beta} \cdot \mathbf{1}(t=r) \\
&\leq \sum_{r=1}^{\infty} \mathbb{E} \Gamma_{d(r+1)}^{2\beta/p} \frac{1}{\alpha^\beta} \cdot \mathbf{1}(t=r) = \alpha^{-\beta} \sum_{r=1}^{\infty} \Gamma_{d(r+1)}^{2\beta/p} \cdot q(1-q)^{r-1}.
\end{aligned}$$

But  $\mathbb{E} \Gamma_k^r = k(k+1) \dots (k+r-1) \leq (k+r-1)^r$  for  $k, r \in \mathbb{N}$  (see Fisz [2]). Thus

$$\mathbb{E} \Gamma_{d(r+1)}^{2\beta/p} \leq \mathbb{E} \Gamma_{d(r+1)}^{[2\beta/p]} + 1 \leq \left( d(r+1) + \frac{2\beta}{p} \right)^{(2\beta/p)+1} + 1$$

and

$$\sum_{r=1}^{\infty} \mathbb{E} (\Gamma_{d(r+1)}^{2\beta/p}) q(1-q)^{r-1} \leq 1 + \sum_{r=1}^{\infty} \left( d(r+1) + \frac{2\beta}{p} \right)^{(2\beta/p)+1} \cdot q(1-q)^r,$$

whence

$$\mathbb{E} \lambda_d^{-2\beta} \leq C_d \alpha^{-\beta} \cdot W_\beta(1-q),$$

where

$$W_\beta(x) = 1 + \sum_{r=1}^{\infty} \left( d(r+1) + \frac{2\beta}{p} \right)^{(2\beta/p)+1} \cdot x^r, \quad |x| < 1.$$

Now we have to prove the following

**FACT 3.** Let  $\sigma$  be a spectral measure such that  $\tau(\sigma) > 0$ . Define

$$U(\sigma) = \{(\alpha, q): P(|\det [Z_1, \dots, Z_d]| > \alpha) = q\}$$

and

$$M_\varepsilon = \{\sigma: \tau(\sigma) \geq \varepsilon, \text{supp } \sigma = S^{d-1}, \sigma(S^{d-1}) = 1\}.$$

Then

$$\sup_{\sigma \in M_\varepsilon} \inf_{(\alpha, q) \in U(\sigma)} \frac{1}{\alpha^\beta} W_\beta(1-q) < \infty.$$

**Proof.** In Fact 2 we have proved that, for  $\sigma \in M_\varepsilon$ ,

$$\inf_{(\alpha, q) \in U(\sigma)} \frac{1}{\alpha^\beta} W_\beta(1-q) < \infty.$$

Let  $\sigma_n \in M_\varepsilon$  be such that

$$\inf_{(\alpha, q) \in U(\sigma_n)} \frac{1}{\alpha^\beta} W_\beta(1-q) \rightarrow \infty \quad \text{as } n \rightarrow \infty.$$

By Fact 1 we can choose a subsequence  $\sigma_{n_k} \xrightarrow{w} \sigma_0$ ,  $\sigma_0 \in M(\varepsilon)$ . From Fact 2 we deduce that there exists  $\alpha_0$  such that

$$P_{\sigma_0}(|\det [Z_1, \dots, Z_d]|^2 > \alpha_0) > 0 \quad \text{and} \quad P_{\sigma_0}(|\det [Z_1, \dots, Z_d]|^2 = \alpha_0) = 0,$$

$P_{\sigma_0}$  denotes such a measure that  $\mathcal{L}(Z_i) = \sigma_0$ . Since  $\sigma_{n_k} \rightarrow \sigma_0$ ,  $\det[x_1, x_2, \dots, x_d]$  is continuous, we have

$$\lim_{n \rightarrow \infty} P_{\sigma_{n_k}}(|\det[Z_1, \dots, Z_d]|^2 > \alpha_0) = P_{\sigma_0}(|\det[Z_1, \dots, Z_d]|^2 > \alpha_0),$$

and thus

$$\limsup \frac{1}{\alpha_0^\beta} W_\beta (1 - P_{\sigma_n}(|\det[Z_1, \dots, Z_d]|^2 > \alpha_0)) < \infty.$$

This completes the proof.

Recall that  $\mu(\cdot) = E\mu_{(r,Z)}(\cdot)$ . Denote by  $f_{(r,Z)}(x)$  the density of a Gaussian measure  $\mu_{(r,Z)}$ . If  $f(x)$  is the density of  $\mu$ , then we have  $f(x) = E f_{(r,Z)}(x)$ .

FACT 4. For  $n \in N$ ,  $a \in S^{d-1}$ ,

$$(a) \quad D_a^n f(x) = E D_a^n f_{(r,Z)}(x),$$

and for every  $0 < \varepsilon < 1$ ,  $x \neq 0$ ,

$$(b) \quad |D_a^n f_{(r,Z)}(x)| \leq \frac{C_{n,\varepsilon} \lambda_1}{|x| \lambda_d^n} f_{(r,Z)}(\sqrt{1-\varepsilon}x).$$

Proof. (a) We have

$$f_{(r,Z)}(x) = \frac{1}{(2\pi)^{d/2} \lambda_1 \dots \lambda_d} \exp\left(-\frac{1}{2} \sum \frac{\langle v_i, x \rangle^2}{\lambda_i^2}\right).$$

First of all we prove that

$$(*) \quad \sup_{|t| \leq 1} |[e^{h(t)}]^{(n)}| \leq \left(n + \frac{1}{\lambda_d^2} (d|x|+1)\right)^n, \quad \text{where } h(t) = -\frac{1}{2} \sum \frac{\langle v_i, x+ta \rangle^2}{\lambda_i^2}.$$

Put  $G_n(t)$  such that  $e^{h(t)} \cdot G_n(t) = [e^{h(t)}]^{(n)}$ . Therefore,  $G_{n+1} = h'(t) \cdot G_n(t) + G_n'(t)$ . The function  $G_n(t)$  is a polynomial of degree  $n$ ,  $G_n(t) = a_0 + a_1 t + \dots + a_n t^n$ ; putting  $|G_n| = |a_0| + |a_1| + \dots + |a_n|$ , we get

$$|G_{n+1}| \leq |h'| \cdot |G_n| + n|G_n| = |G_n|(|h'| + n) \quad \text{and} \quad |G_n| \leq (n + |h'|)^n.$$

Now

$$\begin{aligned} h'(t) &= \left( -\frac{1}{2} \sum \frac{\langle v_i, x \rangle^2 + 2t \langle v_i, x \rangle \langle v_i, a \rangle + t^2 \langle v_i, a \rangle^2}{\lambda_i^2} \right)' \\ &= -\sum \left[ \frac{\langle v_i, x \rangle \langle v_i, a \rangle}{\lambda_i^2} + t \frac{\langle v_i, a \rangle^2}{\lambda_i^2} \right], \\ |h'| &\leq \frac{1}{\lambda_d^2} \sum |\langle v_i, x \rangle \langle v_i, a \rangle| + \langle v_i, a \rangle^2 \leq \frac{1}{\lambda_d^2} (|x|d + 1) \end{aligned}$$



because  $\sum \langle v_i, a \rangle^2 = |a|^2 = 1$  and  $|\langle v_i, x \rangle \langle v_i, a \rangle| \leq |x|$ . Thus

$$\sup_{|t| \leq 1} |[e^{h(t)}]^{(n)}| \leq \sup_{|t| \leq 1} |G_n(t) \cdot e^{h(t)}| \leq |G_n| \leq \left( n + \frac{1}{\lambda_d^2} (d|x| + 1) \right)^n,$$

which proves (\*).

Now we are ready to prove (a); the proof goes by an easy induction.

For  $n = 1$

$$\left| \frac{f_{(r,z)}(x+ta) - f_{(r,z)}(x)}{t} \right| = \left| \frac{d}{dt} f_{(r,z)}(x+ta) \Big|_{t=\lambda} \right| \leq \frac{1}{(2\pi)^{d/2} \lambda_d^d} \left( 1 + \frac{1}{\lambda_d^2} (d|x| + 1) \right).$$

Using the Lebesgue Dominated Convergence Theorem we get

$$\lim_{t \rightarrow 0} \frac{f(x+ta) - f(x)}{t} = \lim_{t \rightarrow 0} E \frac{f_{(r,z)}(x+ta) - f_{(r,z)}(x)}{t} = E D_a^{(1)} f_{(r,z)}(x)$$

because, by Lemma 2,  $1/\lambda_d$  has all positive moments.

Similar arguments show that

$$\begin{aligned} & \left| \frac{D_a^n f_{(r,z)}(x+ta) - D_a^n f_{(r,z)}(x)}{t} \right| \\ &= |[f_{(r,z)}(x+ta)]^{(n+1)}| \leq \left( n + 1 + \frac{1}{\lambda_d^2} (d|x| + 1) \right)^{n+1} \frac{1}{\lambda_d^d (2\pi)^{d/2}}. \end{aligned}$$

By the Lebesgue Theorem and Lemma 2 we get the desired result.

(b) For a moment denote a scalar product by

$$\langle x, y \rangle_1 = \sum_{i=1}^d \frac{\langle v_i, x \rangle \langle v_i, y \rangle}{\lambda_i^2},$$

put  $g_{(r,z)}(x) = \exp(-\frac{1}{2}|x|_1^2)$  and

$$g_{(r,z)}(x+ta) = \exp(-\frac{1}{2}\langle x+ta, x+ta \rangle_1) = \exp(-\frac{1}{2}|x|_1^2 - t\langle x, a \rangle_1 - \frac{1}{2}t^2\langle a, a \rangle_1).$$

Let us compute

$$\begin{aligned} & \frac{d^n}{dt^n} g_{(r,z)}(x+ta) \Big|_{t=0} = \exp(-\frac{1}{2}|x|_1^2) \cdot [\exp(-t\langle x, a \rangle_1) \cdot \exp(-\frac{1}{2}t^2\langle a, a \rangle_1)]^{(n)} \\ &= \exp(-\frac{1}{2}|x|_1^2) \left( \sum_{\substack{k=0 \\ n-k \text{ even}}}^n \binom{n}{k} (\exp(-t\langle x, a \rangle_1))^{(k)} \cdot (\exp(-\frac{1}{2}t^2\langle a, a \rangle_1))^{(n-k)} \right). \end{aligned}$$

Hence

$$|(g_{(r,z)}(x+ta))_{t=0}^{(n)}| \leq \exp(-\frac{1}{2}|x|_1^2) \cdot C_n \left( \sum_{\substack{k=0 \\ n-k \text{ even}}}^n |\langle x, a \rangle_1|^k (\langle a, a \rangle_1)^{(n-k)/2} \right)$$

$$\begin{aligned} &\leq g_{(r,z)}(x) \cdot C_n \left( \sum_{k=0}^n |x|_1^k |a|_1^n \right) \leq C_n g_{(r,z)}(x) |a|_1^n \left( \sum_{k=0}^n |x|_1^k \right) \\ &\leq C_{n,\varepsilon} \frac{1}{\lambda_d^n |x|_1} \exp\left(-\frac{1}{2}(1-\varepsilon)|x|_1^2\right) \leq \frac{C_{n,\varepsilon} \lambda_1}{|x| \lambda_d^n} \exp\left(-\frac{1}{2}(1-\varepsilon)|x|_1^2\right) \end{aligned}$$

and, finally,

$$|D_a^{(n)} f_{(r,z)}(x)| \leq \frac{C_{n,\varepsilon} \lambda_1}{|x| \lambda_d^n} f_{(r,z)}(\sqrt{1-\varepsilon} x).$$

Now we are able to prove Theorem 1. From Fact 4 we infer that for every  $0 < \varepsilon < 1$

$$|D_a^{(n)} f(x)| \leq E \frac{C_{n,\varepsilon} \lambda_1}{|x| \lambda_d^n} \frac{\exp\left(-\frac{1}{2}(1-\varepsilon)|x|_1^2\right)}{(2\pi)^{d/2} \lambda_1 \cdots \lambda_d}.$$

Using the Hölder inequality to the above inequality with  $p = 1/(1-\varepsilon)$  and  $q = 1/\varepsilon$ , we get

$$\begin{aligned} |D_a^{(n)} f(x)| &\leq \frac{C_{n,\varepsilon}}{|x|} \left[ E \left( \frac{\lambda_1}{\lambda_d^n} \right)^{1/\varepsilon} \frac{1}{\lambda_1 \cdots \lambda_d} \right]^\varepsilon \left[ E \frac{\exp\left(-\frac{1}{2}|x|_1^2\right)}{(2\pi)^{d/2} \lambda_1 \cdots \lambda_d} \right]^{1-\varepsilon} \\ &\leq \frac{C_{n,\varepsilon}}{|x|} [E \lambda_1^{1/\varepsilon-1} \cdot \lambda_d^{-n/\varepsilon-(d-1)}]^\varepsilon [f(x)]^{1-\varepsilon}, \end{aligned}$$

where we have used the fact that

$$f(x) = E f_{(r,z)}(x) \quad \text{and} \quad f_{(r,z)} = \frac{\exp\left(-\frac{1}{2}|x|_1^2\right)}{(2\pi)^{d/2} \lambda_1 \cdots \lambda_d}.$$

Further:

$$E \lambda_1^{1/\varepsilon-1} \cdot \lambda_d^{-[n/\varepsilon+d-1]} \leq (E \lambda_1^{u(1/\varepsilon-1)})^{1/u} (E \lambda_d^{-(n/\varepsilon+d-1)u})^{1/u^*}$$

if  $u(1/\varepsilon-1) < p$  (Lemma 1) and  $u > 1$  with  $1/u + 1/u^* = 1$ .

This implies that  $1 < u < \varepsilon(1-\varepsilon)^{-1} p$ , so that we can find such  $u$  if  $\varepsilon(1-\varepsilon)^{-1} p > 1$ . Hence

$$0 < 1-\varepsilon < 1 - \frac{1}{1+p} = \frac{p}{1+p}.$$

To complete our proof we have to show that

$$(1) \inf_{\sigma \in M_\varepsilon} \inf_{|x| \leq 1} f_\sigma(x) > 0,$$

(2)  $\sup_{\sigma \in M_\varepsilon} \sup_{|x| \leq 1} \sup_{a \in S^{d-1}} |D_a^{(n)} f_\sigma(x)| < \infty$ , where  $M_\varepsilon = \{\sigma: \tau(\sigma) \geq \varepsilon\}$  and  $f_\sigma(x)$  is the density of  $p$ -stable measure with spectral measure  $\sigma$ .

The function  $(\sigma, x) \rightarrow f_\sigma(x)$  is continuous because its Fourier transform is less than  $\exp(-\varepsilon|x|^p)$ . Since  $M_\varepsilon$  is compact,  $\inf_{\sigma \in M_\varepsilon} \inf_{|x| \leq 1} f_\sigma(x) = f_{\sigma_0}(x_0)$  for certain  $\sigma_0 \in M_\varepsilon$  and  $|x_0| \leq 1$ . But  $p$ -stable densities are always positive for every  $x \in \mathcal{R}^d$ .

By similar arguments we obtain

$$\sup_{\sigma \in M_\varepsilon} \sup_{|x| \leq 1} \sup_{a \in S^{d-1}} |D_a^{(m)} f_\sigma(x)| = |D_{a_0}^{(m)} f_{\sigma_0}(x_0)| < \infty$$

for certain  $\sigma_0 \in M_\varepsilon$ ,  $|x_0| \leq 1$ , and  $a_0 \in S^{d-1}$ .

**Applications.** We will use our inequality to a problem of admissible translates. Recall that two probability measures  $\tau, \nu$  are *equivalent* ( $\tau \sim \nu$ ) if, for every measurable set  $A$ ,  $\mu(A) = 0$  if and only if  $\nu(A) = 0$ . We write  $\mu \perp \nu$  if there exists  $A$  such that  $\mu(A) = 1$  and  $\nu(A) = 0$ . A vector  $a$  is an *admissible translate* of  $\mu$  if  $\mu(\cdot - a) \sim \mu(\cdot)$ .

Let us consider the series  $\sum (X_n \cos 2\pi nt + Y_n \sin 2\pi nt)$  in  $L_2([0, 1], dx)$ , where  $(X_n, Y_n)_{n=1}^\infty$  are independent 2-dimensional variables. Since the functions  $X_n \cos 2\pi nt + Y_n \sin 2\pi nt$  belong to mutually orthogonal subspaces of  $L_2$ , we consider

$$\mu = \prod_{n=1}^\infty \mu_n, \quad \text{where } \mu_n = \mathcal{L} \left( \frac{X_n}{\sigma_n^{1/p}(S)}, \frac{Y_n}{\sigma_n^{1/p}(S)} \right)$$

on  $(\mathbb{R}^2)^N$ , and  $\sigma_n$  is the spectral measure of  $\mathcal{L}(X_n, Y_n)$ .

The problem is the following: find all vectors  $\underline{a} = (a_1, a_2, \dots)$  such that the measures  $\mu(\cdot - \underline{a})$  and  $\mu(\cdot)$  are equivalent. The question was investigated in [7] and [10], but only in the case when  $\mu_n$  are 1-dimensional.

For the sake of completeness we recall below some basic facts and theorems (see Shepp [9]).

If  $\mu, \nu$  are any probability measures, then there exists a measure  $m$  such that  $m \gg \mu$  and  $m \gg \nu$  (for example,  $m = \frac{1}{2}(\mu + \nu)$ ). In this case  $\varphi(x) = d\mu/dm$  and  $\psi(x) = d\nu/dm$ . Let us put

$$H(\mu, \nu) = \int \sqrt{\varphi(x) \cdot \psi(x)} dm.$$

Observe that  $H(\mu, \nu)$  does not depend on the choice of measure  $m$  and, by the Schwarz inequality,  $0 \leq H(\mu, \nu) \leq 1$ .

**THEOREM (Kakutani [4]).** Put  $\mu = \prod_{n=1}^\infty \mu_n$  and  $\nu = \prod_{n=1}^\infty \nu_n$ , where  $\mu_n$  and  $\nu_n$  are probability measures. Then

$$H(\mu, \nu) = \prod_{n=1}^\infty H(\mu_n, \nu_n).$$

Moreover,  $\mu \perp \nu$  if and only if  $H(\mu, \nu) = 0$ . If  $\mu_n \sim \nu_n$ ,  $n = 1, 2, \dots$ , then  $\mu \sim \nu$  if and only if  $H(\mu, \nu) > 0$ .

The Kakutani Theorem implies that if  $\mu_n \sim \nu_n$ , then  $\mu \perp \nu$  or  $\mu \sim \nu$ .

Now we repeat some observations of Shepp [9]. Let  $\mu$  be a measure on  $\mathbb{R}^2$  with density  $\varphi(x)$ , and  $\varphi(x) > 0$  for almost all  $x$  with respect to Lebesgue measure. Since

$$H(\mu, \mu(\cdot - a)) = \int \sqrt{\varphi(x) \cdot \varphi(x-a)} dx = \int \sqrt{\varphi(x)} \cdot \sqrt{\varphi(x-a)} dx,$$

$\sqrt{\varphi} \in L_2(dx)$ , we have by Parseval's identity

$$\begin{aligned} \int \sqrt{\varphi(x)} \cdot \sqrt{\varphi(x-a)} dx &= (2\pi)^{-2} \int (\sqrt{\varphi})^\wedge (\sqrt{\varphi(x-a)})^\wedge dx \\ &= (2\pi)^{-2} \int_{\mathcal{R}^2} \cos \langle x, a \rangle |(\varphi^{1/2})^\wedge|^2 dx. \end{aligned}$$

But

$$\begin{aligned} 1 - H(\mu, \mu(\cdot - a)) &= (2\pi)^{-2} \int_{\mathcal{R}^2} (1 - \int_{\mathcal{R}^2} (1 - \cos \langle a, x \rangle) |(\varphi^{1/2})^\wedge|^2 dx) \\ &\leq C \int_{\mathcal{R}^2} \langle a, x \rangle^2 |(\varphi^{1/2})^\wedge|^2 dx \\ &= C \int_{\mathcal{R}^2} (i \langle x, a \rangle (\varphi^{1/2})^\wedge) \overline{(i \langle x, a \rangle (\varphi^{1/2})^\wedge)} dx \\ &= C \int_{\mathcal{R}^2} |D_a \varphi^{1/2}|^2 dx = C \int_{\mathcal{R}^2} \left[ \frac{D_a \varphi}{\varphi^{1/2}} \right]^2 dx = C \int_{\mathcal{R}^2} \frac{(D_a \varphi)^2}{\varphi} dx \end{aligned}$$

with

$$C = \frac{1}{8\pi^2} \quad \text{and} \quad D_a \varphi = \lim_{t \rightarrow 0} \frac{\varphi(x+ta) - \varphi(x)}{t}.$$

Thus, if  $\mu = \prod_{n=1}^{\infty} \mu_n$ ,  $\varphi_n = d\mu_n/dx$ ,  $\underline{a} = (a_1, a_2, \dots)$ , and

$$(*) \quad \sum \int_{\mathcal{R}^2} \frac{(D_{a_i} \varphi_i)^2}{\varphi_i^2} dx < \infty,$$

then the measures  $\mu(\cdot - a)$  and  $\mu$  are equivalent. The quantity  $\int ((D_a \varphi)^2 / \varphi) dx$  is called the *Fisher information*.

Now we are ready to prove the following

**THEOREM 2.** *Let  $\mu_n$  be 2-dimensional symmetric  $p$ -stable measures with spectral measures  $\sigma_n$ ,  $1 < p < 2$ . Additionally, we assume that  $\sigma_n(S) = 1$  and  $\inf_n \tau(\sigma_n) > 0$ . Then  $\underline{a} = (a_1, a_2, \dots)$  is an admissible translate of  $\mu$  if and only if  $\sum_i |a_i|^2 < \infty$ .*

**Proof.** First we prove that if  $\underline{a}$  is an admissible translate, then  $\underline{a} \in l_2(N)$ .

Let  $\underline{\mu} = \sum_{n=1}^{\infty} \mu_n$  on  $(\mathcal{R}^2)^N$ . Take any sequence of non-zero vectors in  $\mathcal{R}^2$ , say  $(y_i)$ , define  $T: (\mathcal{R}^2)^N \rightarrow \mathcal{R}^N$ , where for  $\underline{x} = (x_1, x_2, \dots) \in (\mathcal{R}^2)^N$

$$T(\underline{x}) = \left( \left\langle \frac{y_1}{|y_1| \sigma_1}, x_1 \right\rangle, \left\langle \frac{y_2}{|y_2| \sigma_2}, x_2 \right\rangle, \dots \right),$$

and  $\langle \cdot, \cdot \rangle$  denotes scalar product;  $|y_i| \sigma_i > 0$  because  $\inf_n \tau(\sigma_n) > 0$ . Since  $T$  is measurable and linear, we can define

$$\underline{\mu}_T(A) = \underline{\mu}(T^{-1}(A)) = \prod_{n=1}^{\infty} \mu_{y_i}$$

and

$$\underline{\mu}_T^a(A) = \mu(T^{-1}(A) - \underline{a}) = \prod_{n=1}^{\infty} \mu_{y_n}(\cdot - T(\underline{a})_n),$$

where

$$\mu_{y_i}(A) = \mu_i \left( \left\langle \frac{y_i}{|y_i|_{\sigma_i}}, \cdot \right\rangle^{-1}(A) \right) \quad \text{and} \quad T(\underline{a}) = (T(\underline{a})_1, \dots).$$

Measures  $\mu_{y_i}$  are 1-dimensional  $p$ -stable with unit spectral measure (equivalently, for every  $n$ ,  $\int e^{itx} \mu_{y_n}(dx) = \exp(-|t|^p)$ ). Further, measures  $\underline{\mu}_T^a$  and  $\underline{\mu}_T$  on  $\mathcal{R}^N$  are also equivalent (as images of equivalent measures). Hence  $(T(\underline{a})_1, T(\underline{a})_2, \dots)$  is an admissible translate, and using Proposition 8 from Zinn [10] we infer that

$$\sum_{i=1}^{\infty} \frac{\langle y_i, a_i \rangle^2}{|y_i|_{\sigma_i}^2} < \infty$$

for every sequence  $(y_1, y_2, \dots)$ . Putting  $y_i = a_i$  we get

$$\sum_{i=1}^{\infty} \frac{(a_i, a_i)^2}{|a_i|_{\sigma_i}^2} < \infty.$$

Since  $|a_i|_{\sigma_i}^2 \leq |a_i|^2$ , we obtain also  $\sum_{i=1}^{\infty} (a_i, a_i) < \infty$ .

Now we prove that if  $\sum_{i=1}^{\infty} (a_i, a_i) < \infty$ , then  $\underline{a} = (a_1, a_2, \dots)$  is an admissible translate.

By (\*) we have to calculate

$$\int \frac{(D_{a_i} \varphi_i)^2}{\varphi_i} dx = |a_i|^2 \int \frac{(D_{a_i/|a_i|} \varphi_i)^2}{\varphi_i} dx.$$

We will prove that

$$\sup_i \sup_{\underline{a} \in \mathcal{S}} \int \frac{(D_{\underline{a}} \varphi_i)^2}{\varphi_i} dx < \infty \quad \text{if only} \quad \inf_i \tau(\sigma_i) > 0.$$

From our inequality (Theorem 1), if we take  $0 < \alpha < (p-1)/2p$ , we get

$$\int \frac{(D_{\underline{a}} \varphi)^2}{\varphi} dx \leq \int \frac{C(\tau, \alpha)}{(1+|x|)^2} [\varphi(x)]^{2(1-\alpha)[p/(1+p)]-1} dx = C(\tau, u) \int \frac{1}{(1+|x|)^2} [\varphi(x)]^u dx,$$

where  $0 < u < (p-1)/(p+1)$ .

Let  $k$  be any number such that  $k > (1+p)/(p-1)$  and  $u = 1/k$ . Then  $k^* > 1$ , where  $1/k^* + 1/k = 1$ . Using the Hölder inequality with  $k$  and  $k^*$ , we get

$$\int \frac{1}{(1+|x|)^2} [\varphi(x)]^u dx \leq \left( \int \frac{1}{(1+|x|)^{2k^*}} dx \right)^{1/k^*} \left( \int [\varphi(x)]^{uk} dx \right)^{1/k} < \infty$$

because

$$\int \frac{1}{(1+|x|)^{2k^*}} dx < \infty \quad \text{and} \quad \int \varphi(x) = 1.$$

Finally,

$$\sup_{a \in S} \int \frac{(D_a, \varphi_i)^2}{\varphi_i} dx \leq \left( \int \frac{1}{(1+|x|)^{2k^*}} dx \right)^{1/k^*} C(\tau(\sigma_i), u)$$

and (Fact 3)

$$\sup_{\tau(\sigma_i) \geq \inf_n \tau(\sigma_n)} C(\tau(\sigma_i), u) < \infty.$$

This completes the proof.

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