On Robust Statistics for GNSS Single Point Positioning

Daniel Medina¹, Haoqing Li², Jordi Vilà-Valls³ and Pau Closas²

Abstract—Navigation problems are generally solved applying least-squares (LS) adjustments. Techniques based on LS can be shown to perform optimally when the system noise is Gaussian distributed and the parametric model is accurately known. Unfortunately, real world problems usually contain unexpectedly large errors, so-called outliers, that violate the noise model assumption, leading to a spoiled solution estimation. In this work, the framework of robust statistics is explored in order to provide a robust solution to the Global Navigation Satellite Systems (GNSS) single point positioning (SPP) problem. Considering that GNSS observables may be contaminated by erroneous measurements, we survey most popular approaches for robust regression and how they can be adapted into a general methodology for robust SPP.

I. INTRODUCTION

Global Navigation Satellite Systems (GNSS) play a fundamental role on prospective applications of Intelligent Transportation Systems (ITS), as the main source of positioning information. Besides, GNSS provides timing synchronization ranging from 10 to 40% of different magnitude. Finally, Gaussian efficiency and the capability of mitigating the effects of outliers is addressed over different data sizes, to verify the importance of data redundancy for the performance of robust estimators.

The rest of the paper is organized as follows. In Section

This work has been partially supported by the DGA/MRIS (2018.60.0072.00.470.75.01) and NSF under Awards CNS-1815349 and ECCS-1845833.

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2, the basics of robust estimation are introduced. Section 3 relates the specific implementation details of using robust techniques in the GNSS single point positioning problem. Section 4 present the simulation results and discusses the performance of robust estimators. Finally, in Section 5 the outlook along with the next steps on the future work are presented.

II. BACKGROUND ON ROBUST ESTIMATION

A traditional way to represent ‘well-behaved’ data is to assume that the underlying noise is normal distributed, with known parametrization,

\[ \varepsilon \sim \mathcal{N}(\mu, \sigma^2) . \tag{1} \]

Thus, classical regression methods assume that \( \varepsilon \) belongs to an exactly known parametric distribution [30]. If this assumption holds, the LS estimate is optimal. However, in many practical situations Gaussianity does not hold and we may speak of approximately normal measurements, for instance due to larger probability of observations occurring at the tails of the distribution. In those circumstances, the aforementioned optimality is lost for LS, and robust estimators become relevant to provide close-to-optimal results in non-normal conditions. The concept of approximate normality can be formalized by considering that a proportion \( 1 - \epsilon \) of the observations are affected by Gaussian noise, while with complementary probability \( 0 \leq \epsilon \leq 1 \) the data is contaminated by an unknown (potentially) non-Gaussian distribution,

\[ \varepsilon \sim (1 - \epsilon) G + \epsilon H \tag{2} \]

where \( G = \mathcal{N}(\mu, \sigma^2) \) is the nominal Gaussian distribution and \( H \) is an arbitrary contaminating distribution. Notice that another approach for modeling outliers involves the use of heavy-tailed distributions, whose tails tend to zero at a slower rate than the Gaussian distribution. Cauchy, Laplace, Student-t or \( \alpha \)-stable distributions are examples of such heavy-tailed densities. This section introduces a basic notion on robust statistics and on some of the most well-known robust estimators for regression problems. For a detailed theoretical analysis of robust statistics, the reader is referred to classical textbooks [10], [31], [32], or the recent works [11], [33] for its application to a variety of signal processing problems.

A. Robust Statistics Dictionary

Some basic concepts from robust statistics are introduced in this section. First we define qualitative robustness adopting Hampel’s definition [8]. In plain words, if a bounded change in the distribution of the observations is seen as a bounded change in the distribution of the estimates, then the claim is that the estimator is robust. More precisely, let \( \mathcal{X} = \{x_1, \ldots, x_n\} \) be a set of i.i.d. observations from a distribution \( F \), and let \( T_n = T_n(\mathcal{X}) \) be a sequence of estimates. Then \( T_n \) is called robust at \( F = F_0 \) if the sequence of maps of distributions \( ^1\mathcal{E}_F(T_n) \) is equicontinuous at \( F_0 \), that is, if we take a suitable distance \( d_* \), in the space of probability measures, and assume that for all \( \delta_1 > 0 \) there exists a \( \delta_2 > 0 \) such that,

\[ d_*(F_0, F) \leq \delta_1 \Rightarrow d_*\left(\mathcal{E}_{F_0}(T_n), \mathcal{E}_{F}(T_n)\right) \leq \delta_2 . \tag{3}\]

Another important metric is the breakdown point \( \epsilon^* \), which was first defined as the smallest percentage of contamination that can cause the estimator to take on arbitrarily large aberrant value [8]. Later, the concept of breakdown point on finite sets was introduced in [34]. Thus, take any sample \( \mathcal{X} \) of \( n \) observations and any estimator \( T \hat{} = T_n \). Let \( \beta(m, T, \mathcal{X}) \) be the supremum of \( ||T(\mathcal{X'}) - T(\mathcal{X})|| \) for all corrupted samples \( \mathcal{X'} \) where \( m \) of the original \( n \) observations are replaced by arbitrary values. Then, the breakdown point of an estimator \( T \) is defined as

\[ \epsilon^*_{m}(T, \mathcal{X}) = \min \left\{ \frac{m}{n}, \beta(m, T, \mathcal{X}) \right\} . \tag{4}\]

If a set of observation is to follow a mixture model as in Eq. 2, those healthy observations following a known distribution are referred to as inliers. On the other hand, observations that are well separated from the majority of the data are generally referred to as outliers within the framework of robust statistics.

Robust estimators provide resiliency to outliers, but they do it at the price of some performance degradation under the nominal model, that is when all observations are inliers. The way to quantify such degradation is through the so-called loss-of-efficiency (LoE), that is defined as the ratio of performances between the optimal method (e.g., the LS) and the robust estimator, both using measurements from the nominal model, \( \epsilon = 0 \).

B. Robust Estimates for Regression Problems

Consider a linear regression problem \( y_i = z_i^\top x + n_i \), with \( t = 1, \ldots, N \), and \( x \) a parameters vector to be estimated, or in vector form, \( y = Zx + n \). We can define a vector \( r = y - Zx \) of observation residuals. The regression is generally solved applying a LS estimator (minimization of the \( \ell_2 \)-norm of the residuals),

\[ \hat{x}_{LS} = \arg \min_x ||y - Zx||_2^2 = \arg \min_x \sum_{i=1}^N \left(\frac{r_i(x)}{\sigma_i}\right)^2 , \tag{5}\]

which is optimal when the Gaussian noise assumption for \( n \) holds. However, it lacks robustness as even a single outlier could completely spoil the estimation. A first approach towards protecting against outlying measurements is the least-absolute value or \( \ell_1 \), consisting on the substitution of the squared residuals as

\[ \hat{x}_{\ell_1} = \arg \min_x \sum_{i=1}^N \left|\frac{r_i(x)}{\sigma_i}\right| . \tag{6}\]

Nonetheless, the \( \ell_1 \) method retains a sum of residuals and thus the influence of outliers is still unbounded. This problem can be generalized by considering a general loss function \( \rho(x) \) (a.k.a. \( \rho \)-function). For instance, \( \rho_{LS}(x) = x^2 \) and \( \rho_{\ell_1}(x) = |x| \) correspond to the aforementioned estimation
approaches. The framework of robust statistics proposes loss functions \( \rho (\cdot) \) such that the estimates are nearly optimal when the noise is exactly normal and nearly optimal when the noise is approximately normal (e.g., contaminated normal). We define \( \psi (x) = \frac{\partial \rho (x)}{\partial x} \), called the influence function (a.k.a. \( \psi \)-function). Several robust estimators of regression have been proposed in the literature, the most popular being: i) M-estimate, ii) S-estimate, and iii) MM-estimate. In the sequel, the loss functions for robust statistics are introduced, alongside some details on the robust estimators, for which Fig. 1 provides some pictorial support.

1) Huber and Tukey Families of Loss Functions: The key idea behind robust estimation is to use loss functions which appropriately penalize measurements with outliers. Several loss functions exist in the literature, the most common being Huber and Tukey’s bisquare families of functions. The family of Huber functions is defined as

\[
\rho^H_a(x) = \begin{cases} 
  x^2, & \text{if } |x| \leq a \\
  2a|x| - a^2, & \text{if } |x| > a,
\end{cases}
\]

and

\[
\psi^H_a(x) = \begin{cases} 
  x, & \text{if } |x| \leq a \\
  a \text{sgn}(x), & \text{if } |x| > a,
\end{cases}
\]

\[
W^H_a(x) = \min \left\{ 1, \frac{a}{|x|} \right\},
\]

then \( \rho^H_a(x) \) is quadratic around 0 and increases linearly with \( x \). In the case of location estimation, the limit cases, \( a \to \infty \) and \( a \to 0 \) correspond to the mean and median estimates, respectively. A desirable property of \( \rho \)-functions is boundedness, which implies redescending \( \psi \)-functions that tend to 0 at infinity. A popular choice is the Tukey’s bisquare or biweight family of functions,

\[
\rho^B_c(x) = \begin{cases} 
  1 - \left( \frac{x}{c} \right)^2, & \text{if } |x| \leq c \\
  1, & \text{if } |x| > c
\end{cases}
\]

\[
\psi^B_c(x) = x \left( 1 - \left( \frac{x}{c} \right)^2 \right) I(|x| \leq c),
\]

\[
W^B_c(x) = \left( 1 - \left( \frac{x}{c} \right)^2 \right) I(|x| \leq c),
\]

with \( c > 0 \) a constant parameter and \( I(|x| \leq c) \) the indicator function, i.e., \( I(|x| \leq c) = 1 \) if \( |x| \leq c \), and 0 if \( |x| > c \).

Typically, the parameter in both functions is fixed to achieve a given efficiency to the normal distribution. For a 95% of efficiency, \( a = 1.345 \) for the Huber function, and \( c = 4.685 \) for the Tukey function.

2) M-estimator: the M-estimate of regression is defined as

\[
\hat{x}_M = \arg \min_x \sum_{i=1}^N \rho \left( \frac{r_i(x)}{\sigma_i} \right),
\]

with \( \bar{\sigma} \), an estimate of the scale of errors \( \sigma_i \), or equivalently, as the solution to

\[
\sum_{i=1}^N \psi \left( \frac{r_i(x)}{\sigma_i} \right) \frac{\partial (r_i(x)/\sigma_i)}{\partial x} = \sum_{i=1}^N \psi \left( \frac{y_i - \hat{x}_M}{\sigma_i} \right) z = 0,
\]

which is commonly solved by an Iteratively Reweighted LS (IRLS), with an instrumental weight function defined as

\[
W(x) = \begin{cases} 
  \psi(x)/x, & \text{if } x \neq 0 \\
  \psi'(0), & \text{if } x = 0
\end{cases}
\]

to provide the convenient alternative formulation,

\[
\sum_{i=1}^N W \left( \frac{r_i}{\sigma_i} \right) \frac{\partial \left( \frac{r_i}{\sigma_i} \right)^2}{\partial x} = 0.
\]

Solving such system requires finding the state estimate per se as well as the weights for each of the observations according to the corresponding weighting function. Notice that a normalization using the dispersion of the residuals \( \sigma_i \) is included in the formulation, because these estimates are not scale equivariant. An estimate of the dispersion must be used, \( \bar{\sigma} \), for instance, the normalized median absolute deviation MAD, defined as

\[
\text{MAD}(x) = c_m \text{Med}(|x - \text{Med}(x)|)
\]

being \( \text{Med}(x) \) the median of \( x \), and \( c_m \) a normalizing constant (\( \approx 1.4815 \) for the normal case).

3) S-estimator: the S-estimate of regression is defined as the estimator that minimizes the robust scale M-estimate,

\[
\hat{x}_S = \arg \min_x s_M(r(x)),
\]

with \( s_M(r(x)) \) the M-estimate of scale, which satisfies

\[
\frac{1}{N} \sum_{i=1}^N \rho \left( \frac{r_i(x)}{s_M(r(x))} \right) = b,
\]

and thus,

\[
\hat{x}_S = \arg \min_x \sum_{i=1}^N \rho \left( \frac{r_i(x)}{\hat{s}} \right), \hat{s} = s_M(r(\hat{x}_S))
\]

Again this is solved by an IRLS. A typical choice is the bisquare scale with \( \rho(x) = \min(1 - (1 - x^2)^2, 1) \) and \( b = 0.5 \). In this case, \( W(x) = \min(3 - 3x^2 + x^4, 1/x^2) \), where it’s clear that larger values of \( x \) have smaller weights. The main problem of S-estimators is that they cannot achieve simultaneously a high BP and high efficiency at the normal distribution.

4) MM-estimator: this robust estimator is designed to achieve both high efficiency and high BP simultaneously. If we consider two bounded loss functions, \( \rho_0 \) and \( \rho_1 \), which satisfy \( \rho_1 < \rho_0 \), then the MM estimator is defined as

\[
\hat{x}_{MM} = \arg \min_x \sum_{i=1}^N \rho_1 \left( \frac{r_i(x)}{s_N(r(\hat{x}_1))} \right),
\]

where \( \hat{x}_1 \) is consistent and high BP estimate of \( x \), and \( s_N(r(\hat{x}_1)) \) is the M-estimate of scale of the residuals of \( \hat{x}_1 \), computed using \( \rho_0 \) and \( b \).

The MM-estimate is build up with three steps:

1) Compute an initial consistent S-estimate of \( x \), \( \hat{x}_1 \), with a high BP but possibly low normal efficiency.

2) Compute a M-estimate of the scale of the residuals \( s_N(r(\hat{x}_1)) \) using the high BP estimate \( \hat{x}_1 \).
tion model, the problem is typically linearized and solved of Eq. 23. Since GNSS SPP involves a nonlinear observa-
tion model, and

\[ y_k = h(x) + \varepsilon \]  

(23)

where \( y \) is the \( n \)-dimensional observation vector, \( h(\cdot) \) is the observation model from (22) and \( x = [p^T, c \delta t]^T \) is the state to be estimated. The LS adjustment is the most commonly used method for the estimation of the regression problem of Eq. 23. Since GNSS SPP involves a nonlinear observation model, the problem is typically linearized and solved applying an iterative Gauss-Newton method as follows

\[ \Delta x = (H^T W H)^{-1} H^T W y \]  

(24)

\[ \hat{x}^k = \hat{x}^{k-1} + \Delta x \]  

(25)

where \( H \) is the Jacobian matrix for the observation model, also known as geometry matrix. That linearization is performed around some guess point \( \hat{x}^{k-1} \) for the \( k \)-th iteration of the method, and \( \Delta x \) provides the update for that iteration which will be used to linearize at iteration \( k + 1 \) as in (25).

\( W \) is the weighting matrix for the observations. Classical SPP solutions take \( W \) as the inverse of the observations covariance matrix \( R \). Stochastic modelling of pseudorange observations has been a recurrent topic within the GNSS community. A simplification commonly used is to assume that the observations noise is uncorrelated, zero-mean normal distributed \( \varepsilon_i \sim \mathcal{N}(0, \sigma_i^2) \) [35]. Thus, the covariance is given by

\[ R = W^{-1} = \text{diag}(\sigma_1^2, \ldots, \sigma_n^2) \]  

(26)

where \( \sigma_i^2 \) is derived from combining the uncertainty of the different error sources (satellite ephemeris and clock, ionosphere, troposphere, multipath and receiver noise), as in [36], [37] or from error models dependent on the satellite elevation and/or the signal carrier-to-noise density ratio [38–40].

Algorithm 1 describes the IRLS process for the robust estimation of the GNSS SPP. Notice that WLS (a short for weighted least squares) refers to the iterative Gauss-Newton described in (24)-(25), and MAD is defined in (17). \( N \) and \( \delta \) denote the maximum number of iterations of the iterative Gauss-Newton method and the convergence criteria, respectively. The choice of the influence function and the scale estimate is subject on the robust estimator applied – e.g., for the M-estimator, one might use the Huber function in (8) and the MAD as scale estimate.

Remarkably, there are certain specific challenges associated to the GNSS-based positioning problem that we point out in this paper. On the one hand, the observation model \( h(\cdot) \) is nonlinear. Thus, the IRLS procedure for finding the observations weights based on the M-estimator concatenates with the iterative LS used for dealing with the model nonlinearity. On the other hand, the GNSS problem is characterized by presenting fat data samples, namely, there is a low redundancy of observations. Since generally only around a dozen satellites are tracked and at least four parameters are to be estimated, GNSS SPP constitutes a severe case of low redundancy regression problem [41]. Lastly, the general assumption on robust statistics of independent and identically

![Fig. 1: \( \rho(x) \) (left), \( \psi(x) \) (middle) and \( W(x) \) (right) for: i) \( \ell_2 \)-norm (LS), ii) \( \ell_1 \)-norm, iii) Huber fct with \( a = 1.345 \), and iv) Tukey fct with \( c = 4.685 \).](image-url)
Algorithm 1 IRLS procedure for robust SPP

1: Initial WLS \( \x^0, r^0 \) = \( \arg \min_{\x} \| y - H\x \|_W^{-2} \)
2: Initial scale \( \hat{s}^0 = \text{MAD} (r^0) \)
3: Normalized residuals \( d^0 = r^0 / \hat{s}^0 \)
4: for \( k := 1, 2, \ldots, N \) do
5: \( w^k = \psi (d^{k-1}) / d^{k-1} \)
6: \( W = \text{diag} (w_1^k, \ldots, w_n^k) \)
7: \( \text{WLS} \rightarrow \x^k, r^k \)
8: \( \text{Estimate scale} \rightarrow \hat{s} (r^k) \)
9: \( d^k = r^k / \hat{s}^k \)
10: if \( \| x^k - x^{k-1} \| < \delta \) then
11: \( \text{Stop} \)
12: end if
13: end for

distributed noise is not met for the GNSS case. Not only are GNSS observations noise uniquely described using stochastic models, but the assumption of independent noise can be violated for satellites of similar direction-of-arrival (e.g., for multipath and none line of sight effects), or for all satellites (e.g., under the influence of a jamming attack or an ionospheric storm).

IV. TEST AND RESULTS

The performance of robust estimators, as well as classical LS for GNSS positioning, is compared using a simulation environment. Different % of outlying observations \( \epsilon \) and outlier magnitudes are considered. The magnitude of the outliers \( \alpha \) is defined as the ratio between inlier, or healthy observations, and outliers. The sky plot of the tracked satellite is as shown in Fig. 1 and results are obtained after averaging 10^4 Monte Carlo runs. For large ratios of contaminated data (Figs. 3 (b) and (c)), the characteristics of the estimators become more evident. Since the Huber function applied the M estimation is not redescending – i.e., the effects of the outliers do not get completely eliminated –, the performance of the M estimation rapidly decays. On the contrary, the S and MM estimators make use of the Tukey function, which utterly bounds the effects of the observations presenting the largest residuals. Fig. 3 (c) makes evident the need for observation redundancy to ensure the correct functioning of the robust estimators, since the overall positioning performance gets heavily degraded. Nonetheless, the differences on performance between the M-, S- and MM-estimators support the hypothesis suggested on classical robust theory, for which the S- and MM-estimators pose a higher breakdown point compared to the M-estimator.

Given the prospective scenario in which four GNSS constellations will be fully deployed, it results of great interest the performance characterization of robust estimators under a large number of observations available. Thus, a second experiment is carried out by simulating \( n = 40 \) satellites (azimuth \( \sim \mathcal{U} (0, 2\pi) \), elevation \( \sim \mathcal{U} (0, \pi/4) \) and distance \( \sim \mathcal{N} (20.200 [\text{km}], 2.000 [\text{km}^2]) \)). The second row of Fig. 3 shows the positioning performance of the evaluated WLS estimators are the regular WLS, the M estimator on the Huber function (\( \alpha = 1.345 \)), the S estimator on the Tukey function (\( \alpha = 4.685 \) and \( b = 0.5 \)) and the MM estimator (applying on a first stage a S estimator for the scale estimate and later a M estimator, using the same tuning parameters as stated previously). The first row of Fig. 3 shows the positioning root mean squared error (RMSE) on the ordinate axis, and the magnitude of the outliers is depicted on the abscissa axis. As expected, the LS estimation gets spoiled by the contaminated observations, presenting a bias proportional to the size of the outliers. On the other hand, the M,S and MM estimators exhibit certain resilience against the outliers. For a contamination of 10%, the three robust estimators cope perfectly with the contaminated data. Moreover, the performance increases with the size of the outliers, since the detection of these get facilitated by their great impact on the estimation. For large ratios of contaminated data (Figs. 3 (b) and (c)), the characteristics of the estimators become more evident. Since the Huber function applied the M estimation is not redescending – i.e., the effects of the outliers do not get completely eliminated –, the performance of the M estimation rapidly decays. On the contrary, the S and MM estimators make use of the Tukey function, which utterly bounds the effects of the observations presenting the largest residuals. Fig. 3 (c) makes evident the need for observation redundancy to ensure the correct functioning of the robust estimators, since the overall positioning performance gets heavily degraded. Nonetheless, the differences on performance between the M-, S- and MM-estimators support the hypothesis suggested on classical robust theory, for which the S- and MM-estimators pose a higher breakdown point compared to the M-estimator.

Table I: Parameters for the Monte Carlo simulation.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
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<tr>
<td>UTC time</td>
<td>15/05/2017 09:30:00</td>
</tr>
<tr>
<td>Location</td>
<td>Koblenz, Germany (50°21'56&quot;N, 7°35'55&quot;E)</td>
</tr>
<tr>
<td>Number of satellites ( n )</td>
<td>10</td>
</tr>
<tr>
<td>Observation variance noise ( \sigma^2 )</td>
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</tr>
<tr>
<td>Outlier percentage ( \epsilon )</td>
<td>0 - 10 - 20 - 30 - 40</td>
</tr>
<tr>
<td>Outlier magnitude ( \alpha )</td>
<td>1 - 3 - 6 - 10 - 30 - 60 - 100</td>
</tr>
</tbody>
</table>

Fig. 2: Sky plot of the tracked satellites for the simulations.

![Sky plot of the tracked satellites](image-url)
10% of contaminated data.

30% of contaminated data.

40% of contaminated data.

10% of contaminated data.

30% of contaminated data.

40% of contaminated data.

Fig. 3: RMSE positioning error for $\epsilon \in \{10, 30, 40\}$% contamination data (each column) and $n \in \{10, 40\}$ pseudorange observations (each row).

and robust methods. Despite the large of observations, the LS estimation results as spoiled as with a reduced number of measurements, asserting the hypothesis of minimum robustness for classical ML methods. Contrarily, the robust estimators are capable of successfully bounding the effects of outliers, even for the case of 40% data contamination. Again, the S- and MM-estimators manifest the best performance among the robust methods.

Fig. 4: RMSE performance (top) of LS and robust estimators as a function of the number of measurements and loss-of-efficiency (bottom) comparison of robust methods.

Finally, the Gaussian efficiency of the estimators is studied from the point of view of the loss-of-efficiency (LoE). LoE $\in [0, 1)$ is defined as the ratio between the RMSE of the LS and a particular estimator. Given that LS is an optimal estimator for the normal distributed noise, the higher the LoE for an estimator is, the more efficient at normal distribution such estimator is. Fig. 4 (top) depicts the RMSE of the evaluated methods against the number of observations simulated. While in general the positioning improves with the number of measurements, the LoE of an estimator appears detached from the number of observations, as displayed in Fig. 4 (bottom). The S-estimator presents the lowest LoE and, thus, the poorest Gaussian efficiency. On the other hand, the MM-estimator holds a LoE of approximately 0.99 and it represents the most efficient among the compared methods. Given that MM-estimator poses, together with the S-estimator, the best performance against high percentage of contaminated observations, we might conclude that the MM-estimator resembles the best robust method for the GNSS SPP problem.

V. OUTLOOK AND FUTURE WORK

This paper provided an overview of robust statistics and how it can be used to enhance the resilience of single point positioning (SPP) solutions in the presence of outliers, caused in practice by multipath propagation or hardware malfunctioning for instance. SPP can be seen as a regression problem, for which this paper presents its robust version leveraging the sound theory of robust statistics. At the same time, the article discusses the specific aspects of applying robust regression to GNSS SPP solvers, and support the discussion with simulation results showing the improvements of such methods as well as their characterization. Future research will provide a better understanding of the loss-of-efficiency incurred by those methods; as well as the relaxation of the i.i.d. assumption among different satellites,
and the use of robust techniques in recursive versions that yield to more sophisticated PVT solutions.

REFERENCES


