LHC BEAM LOSS PATTERN RECOGNITION

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Abstract

One of the systems protecting CERN’s Large Hadron Collider (LHC) is the Beam Loss Monitoring system (BLM). More than 3600 monitors are installed around the ring. The beam losses are permanently integrated over 12 different time intervals (from 40 microseconds to 84 seconds). When any loss exceeds the thresholds defined for the integration window, the beam is removed from the machine.

Understanding the origin of a beam loss is crucial for machine operation, as it can help to avoid a repetition of the same scenario.

The signals read from given monitors can be considered as entries of a vector. This article presents how a loss map of unknown cause can be decomposed using vector based analysis derived from well-known loss scenarios.

The algorithms achieving this decomposition are described, as well as the accuracy of the results.
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VECTOR DECOMPOSITION

Principle

Let’s consider an ensemble of $m$ monitors, each of them associated with one dimension of a $m$-dimensional vector space. Any loss profile can be expressed as a vector on this space: each coordinate of this vector is the value of the loss recorded by the corresponding monitor.

Let’s consider a group of $n$ known loss scenarios, and the corresponding $n$ vectors ($\vec{v}_i$) expressed on the $m$-dimensional vector space ($n < m$). All vectors only have positive coordinates: the losses are always positive. These vectors can span a subspace of the original vector space but they are not a base: they are neither independent nor orthogonal. Let’s also consider an unknown loss profile, and the corresponding unknown vector $\vec{X}$.

The idea here is to find a linear combination of the vectors ($\vec{v}_i$) that will re-compose the vector $\vec{X}$:

$$\sum_i f_i \cdot \vec{v}_i \approx \vec{X}$$

where the factors ($f_i$) are the scalars of the linear combination. They form a vector of dimension $n$.

The error on the decomposition can be estimated with the difference between the re-composition $\vec{X}^i = M \cdot \vec{F}$ and the original vector $\vec{X}$:

$$e = |\vec{X} - \vec{X}^i|$$

Singular Value Decomposition (SVD)

The problem can be expressed as the matrix equation:

$$M \cdot \vec{F} \approx \vec{X}$$

The matrix $M$ is the matrix formed by the known vectors ($\vec{v}_i$), and we want to determine $\vec{F}$, the factors of the decomposition.

The matrix $M$ must be inverted such that:

$$\vec{F} \approx M^{-1} \cdot \vec{X}$$

One of the techniques used here is called Singular Value Decomposition (SVD) and is the generalisation of the diagonalization of a square matrix, for a non-square matrix. The decomposition is the following [1]:

$$M = U \cdot \Sigma \cdot W^T$$

- $M$ is the original matrix, of size $m \times n$;
- $U$ is an orthogonal unitary matrix, of size $m \times m$;
- $W$ is an orthogonal unitary matrix, of size $n \times n$;
- $\Sigma$ is a non-square diagonal matrix, of size $m \times n$.

$\Sigma$ is such that only the diagonal elements are non-null ($n$ in total) (see Fig. 1). These values ($\lambda_i$) are unique, sorted in decreasing order and are called singular values.

$$\Sigma = \begin{bmatrix} \lambda_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \lambda_n \end{bmatrix}$$

Figure 1: Structure of the $\Sigma$ matrix, for $n < m$. All values are null, apart from the diagonal $\lambda_i = (\Sigma)_{i,i}$.

$U$ and $W$ are orthogonal matrices: they generate an orthonormal base of the corresponding $N$-vector space ($N = n$ or $m$). These vectors are not unique.

Once the matrix $\Sigma_{m \times n}$ has been created, the pseudoinverse $\Sigma^+_{n \times m}$ can be calculated. All values are null, apart from the diagonal ones which are: $(\Sigma^+)_{i,i} = \frac{1}{\lambda_i}$ for $\lambda_i \neq 0$. The pseudoinverse of $M$ is then: $M^+ = W \cdot \Sigma^+ \cdot U^T$.

Gram-Schmidt process

Another way to find the factors of the linear combination is to project the original vector $\vec{X}$ on the vectors ($\vec{v}_i$). Since the vectors ($\vec{v}_i$) don’t form a base of the $m$-vector space, the decomposition is not unique. In order to have

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a unique projection, an orthogonal base is needed. The Gram-Schmidt process is a technique creating an orthogonal set of vectors from a set of non-orthogonal vectors. The technique is to remove the contribution of all previous vectors from the current one. The contribution is the projection of one vector another, calculated with a scalar product. The result for one vector is:

\[ \vec{v}_i' = \vec{v}_i - \sum_{j<i} (\vec{v}_j \cdot \vec{v}_i) \left( \frac{\vec{v}_j}{||\vec{v}_j||} \right) \]

Only the first vector is left unchanged. The result is a set of orthogonal vectors \((\vec{v}_i')\) on which the original vector \(\vec{X}\) can be decomposed. The vectors \((\vec{v}_i)\) are ordered by “closeness to \(\vec{X}\)” (in the sense of the scalar product) before the Gram-Schmidt process. The vector \(\vec{v}_i\) which is the “closest” to \(\vec{X}\) (i.e. the one that maximizes \(\vec{X} \cdot \vec{v}_i\) for \(0 \leq i \leq n\)) will give the highest contribution in \(\vec{X}'\).

**Comparison of the two methods**

The main drawback of the SVD is that the factors can have negative values, which has no physical meaning. The error on the recomposition is usually small: \(||\vec{X} - \vec{X}'|| < 0.1\).

The main drawback of the Gram-Schmidt decomposition is that one factor usually dominates the others, and the error is higher than with the SVD. However, the results are always physical.

**IMPLEMENTATION OF VECTOR DECOMPOSITION**

**Choice of beam loss scenarios**

The goal of this work is to recognize patterns in the losses. The choice was made to start with the typical loss scenarios at Point 7 of the LHC, where most collimators for horizontal (H) and vertical (V) cleaning are installed.

The chosen loss scenarios are the verification measurements of collimation cleaning called loss maps (see Fig. 2). There are four cases: B1H, B1V, B2H, B2V.

The choice was made to normalize all vectors so that they have a euclidean norm equal to 1 in the \(m\)-vector space. This takes into account the normalisation by beam intensity, assuming that losses are proportional to intensity. All 2011 loss maps were gathered, normalised and averaged to create the reference vectors.

**Choice of the list of BLMs**

Here, the interesting BLMs — the ones carrying information about the type of loss — are the BLMs that have a different signal depending on the case. When considering all cases at the same time, the relevant BLMs will be the ones with a high value of normalised standard deviation. When a monitor for one beam is selected, the corresponding monitor for the other beam must be selected as well, because the layout of the LHC is symmetric for beam 1 and beam 2. In total, 42 monitors were selected, including all monitors around primary collimators (TCPs) and around some long absorbers.

**Reproducibility**

Recognizing patterns in the losses is possible if standard loss scenarios can be defined. The reproducibility of the patterns can be evaluated by checking loss maps taken in similar conditions over time (see Fig. 4). The relative standard deviation is always smaller than 5% for the selected BLMs.

**Centers of Mass**

The result of the decomposition — which vector dominates the considered loss — can be cross-checked using only the horizontal and vertical TCPs, by calculating the position of the center of mass (CoM) between the corresponding BLMs. The studies showed that the signal at the H collimators had to be compensated for the signal at the V collimators by a factor \(\alpha \approx 2\) to account for the development.
RESULTS OF THE DECOMPOSITION

An example of the results is presented in Fig. 3. The error is calculated with Eq. 1 and displayed by the red curve. All techniques give the same results: the loss was first dominated by beam 1, quickly turning into beam 2; the horizontal losses always dominated the vertical ones. The centers of mass give the same result.

When the two beams have different loss rates $\frac{dI}{dt}$, the decomposition should be dominated by the beam with higher loss rate. This is also shown by the correlation between the centers of mass calculated for the derivatives of the intensities of both beams and the center of mass as described in Eq. 5 (see Fig. 6).

\[
\text{CoM}_{H/V} = \frac{(1 + \alpha)(v_1 + v_2) - (h_1 + h_2)}{h_1 + h_2 + (1 - \alpha)(v_1 + v_2)} \quad (4)
\]

\[
\text{CoM}_{1/2} = \frac{(h_2 + v_2) - (h_1 + v_1)}{h_1 + v_1 + h_2 + v_2} \quad (5)
\]

Validation of the results

All losses appearing in the LHC come from protons lost from the beam, mostly on collimators. The norm of the loss vector including all LHC BLMs should — if no important loss location is missed, and not too many losses are double-counted — be proportional to $\frac{dI}{dt}$. In addition, the loss rate $\frac{dI}{dt}$ is measured to be mostly proportional to the intensity $I$. Fig. 5 shows that the norm is proportional to the intensity.

\[\text{Fig. 5: Correlation of the norm of the loss vector (for all BLMs in LHC) vs. intensity in both beams. Only the “average” value of the norm correlates with the intensity. The points for higher values of the norm correspond to occasional higher losses, as opposed to “regular” losses that are proportional to the number of protons.}\]

\[\text{Fig. 6: Correlation of the centers of mass, evaluating the distribution of losses between B1 and B2, and the center of masses calculated for the derivative of the intensity of the two beams. -1 represents a loss entirely dominated by B1; +1 a loss entirely dominated by B2. The selected data come from a period where the variation of intensity was higher for B1 than for B2, during the fill #2001.}\]

Conclusion

The first results of the series of mathematical operations referred to as vector decomposition could be linked to simpler physical values such as intensity. This allows some level of confidence on the ability of these methods to separate the types of losses in the LHC. These methods could be used for beam loss diagnostics in real time in the LHC.

REFERENCES
