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DETECTION OF ANOMALIES IN BPM SIGNALS AT THE VEPP-4M

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Abstract

Beam position monitors (BPMs) are widely used for beam diagnostics in particle accelerators. Turn-by-turn (TbT) beam centroid data provide a means to estimate performance-critical accelerator parameters, like betatron frequency and optical functions. Parameter estimation accuracy is heavily related to TbT data quality. BPM faults might lead to erroneous estimation of accelerator parameters and should be accounted for achieving accurate and reliable results. Several anomaly detection methods for TbT data cleaning are considered. Derived features of BPM signals along with their robust dispersion estimation are used to flag faulty BPM signals. Estimated contamination factor is used with unsupervised learning methods (Local Outlier Factor and Isolation Forest). Application of anomaly detection methods for the VEPP-4M experimental TbT data is reported.

INTRODUCTION

The VEPP-4M storage ring [1] is equipped with 54 dual-plane BPMs [2]. The system can provide TbT data with resolution close to 20 µm. TbT data is acquired by excitation of the circulating beam with impulse kickers. To improve the reliability of optics inference, detection of anomalies in BPM signals is required.

Anomaly detection is widely used for TbT data quality control [3, 4]. Anomalies caused by BPM electronics failures might deteriorate the measurements quality of accelerator parameters. To mitigate the effects of anomalies, robust parameter estimators should be used. Flagged BPMs should be excluded at the optics inference stage where it's possible.

Previously BPM signal quality was judged only based on the frequency spread across BPMs during single data acquisition. In this paper extended procedure of anomaly detection at the VEPP-4M is described. This procedure was tested on a large set of measurements and found to be reliable. Results of anomaly detection and classification at the VEPP-4M are reported.

ANOMALY DETECTION LOOP

A schematic view of the anomaly detection loop is shown in Fig. 1. Usable signal length is limited by decoherence. For frequency measurement, 1024 turns are used and 128 turns are used for amplitude and phase computation.

Each signal is split into several overlapping samples of short lengths. This allows generating large data set. Several different features are computed for each normalized sample. These features are used as a measure of samples similarity. Close samples are assumed to have close set of features. Thus, signals with samples containing large deviations of features can be flagged as anomaly candidates. In our case, eight different derived features were tested. Each feature is also processed separately with a threshold detector. This allows defining anomaly score for each signal as the number of samples from a given signal with a feature value above the defined threshold. Anomaly scores across different features are combined to flag anomaly candidates and to estimate the contamination rate of a given measurement. A combination of threshold detectors performs well for anomaly detection in both simulations and experimental data. Robust estimation of feature spread allows to minimize the number of false positive cases.

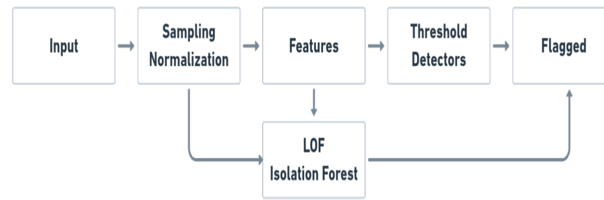

Figure 1: Anomaly detection loop at the VEPP-4M.

For known contamination rate, several unsupervised machine learning (ML) methods can be applied. Local Outlier Factor [5] and Isolation Forest [6] techniques are used as a second layer in anomaly detection. These methods are applied directly to samples and in the feature space. Local Outlier Factor was found to perform well in both cases, while Isolation Forest worked better in feature space.

DERIVED FEATURES GENERATION

For normalized samples, several derived features can be computed. These features are obtained directly from a sample or from a full sample matrix.

Maximum absolute amplitude value in a sample is computed. This feature performs well for identification of spikes in TbT signals. For each sample, the frequency of the largest spectrum peak is computed. Significant frequency deviation across samples might indicate an anomaly and is sensitive to large spikes and noise. Fourier spectrum floor level in a given range of frequencies is used as a next feature. Samples with large noise should have a large spectrum floor level. A selected range of frequencies is assumed to contain no large peaks. Quasiperiodic decomposition reconstruction error is used as a measure of how well a given sample is approximated by several harmonics. From the SVD decomposition of the full sample matrix, the maximum absolute values of SVD space modes are used. Sample noise is also estimated using optimal SVD truncation [7]. Samples with anomalies are assumed to have larger noise estimations. Hankel filter [8] is applied to each sample and a feature is generated as a norm of the difference between filtered and original sample. Robust PCA [9] is used on the full sample matrix.

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Corresponding column norms of the sparse part are used as features. Mean current across BPMs can also be used as an additional feature.

THRESHOLD DETECTORS

Based on a derived feature a simple threshold detector can be constructed. To do this, the median value of sample features is computed or another center tendency estimators can be used. Biweight midvariance is used as a robust estimator of dispersion. The median value is subtracted and absolute values of features are used. Normalization is performed for features and for dispersion estimation. Signal anomaly score is defined the number of samples above certain threshold. In practice, several dispersion values allow reliable separation of outliers. Five dispersion values were used for the VEPP-4M case.

Thus, based on each feature, signals are assigned an anomaly score. Results from all features are combined. If several threshold detectors have zero flagged anomaly candidates, TbT data is considered to be normal. Anomaly scores across detectors are summed and BPMs with total anomaly scores above the given threshold are flagged as anomaly candidates. The contamination rate for a single measurement is estimated based on the flagged signals.

UNSUPERVISED DETECTORS

Local Outlier Factor and Isolation Forest methods are used as an additional layer for anomaly detection. These methods require the expected contamination rate.

The Local Outlier Factor is based on local density estimation. We have tested this method for sample space and derived feature space. It was found to perform well in both cases. For sample space, its performance is influenced by the number of samples. Without splitting BPM signals into a large number of smaller samples, the detection quality was not satisfactory. Several restarts are used to obtain more reliable results.

The Isolation Forest identifies anomalies by isolation. An outlier can be isolated with a smaller number of partitions. When applied to sample space, it was found to produce a large number of false positive results. No such problem was observed for feature space. A random sampling of features with several restarts was used for both methods when applied to features. Instead of using features for each sample, only the largest feature is selected and assigned to the corresponding BPM signal.

ANOMALIES STUDY AT THE VEPP-4M

The above anomaly detection procedure was tested on the VEPP-4M experimental TbT data. Several hundreds of successive data acquisitions were analyzed. Typical examples of BPM signals with anomalies are shown in Fig. 2. Such anomalies are caused by BPM electronics and appear in both planes simultaneously. On average less than 1 % of signals contain such anomalies at beam current in3 mA to 4 mA range and close to 2 % at 1 mA in the first 1024 turns.

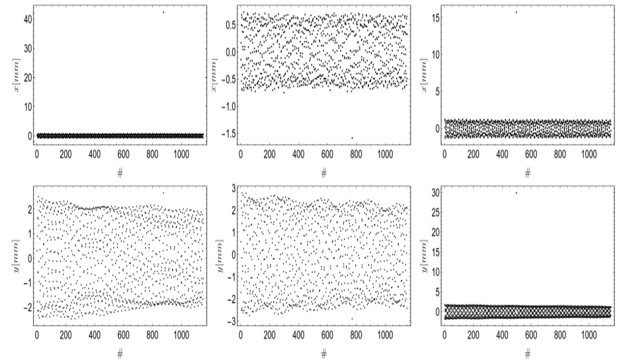

Figure 2: Examples of spike anomalies in TbT signals. Spikes appear in both planes.

In Fig. 3 an example of detected spike anomalies is shown along with derived features for all BPMs. In this measurement, two BPM signals contained spikes in the horizontal plane. As it can be seen, corresponding sample features are well separated from the rest of BPM signals by most of the features. These BPMs were also flagged by ML methods.

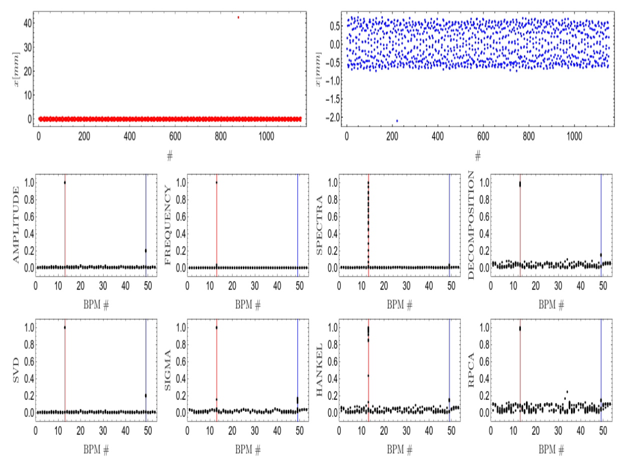

Figure 3: Example of detected spike anomalies from single measurement (top plots). Normalized features for all BPMs (bottom plots). Positions of signals with anomalies are indicated with lines.

Another type of anomalies were observed in both simulations and experimental data in the vertical plane. Several BPM signals were systematically flagged by both layers. These BPMs have small values of vertical β function (1.5 m). And in combination with noise and coupling, they stand out from the rest of BPMs. An example of such systematic anomalies is show in Fig. 4. As it can be seen from feature plots, these signals are separated from other BPMs. Several other BPMs were systematically flagged only by ML methods in the horizontal plane. For these cases, horizontal β function is less than the vertical one. The accuracy of estimated parameters (amplitudes and phases) is poor compared with other BPMs. We exclude these BPMs from the computation of β function based on phase measurement.

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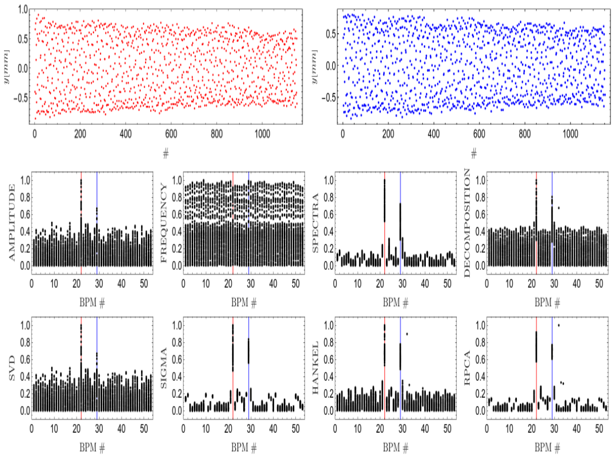

Figure 4: Example of detected systematic anomalies from single measurement (top plots). Normalized features for all BPMs (bottom plots). Positions of signals with anomalies are indicated with lines.

In Fig. 5 the results of 50 successive TbT measurements are shown. BPMs with high counts correspond to systematic anomalies. These BPMs are mostly flagged due to the ratio of β functions. For the horizontal plane, two BPMs stand out. In this case, BPMs are flagged only by ML methods while feature detectors show no sign of anomalies. Normally, since the estimated contamination rate is zero, in this case, used ML methods do not flag any BPMs. But for this study, we have allowed at least one BPM to have an anomaly. For the vertical plane, both layers mostly flag BPMs in the experimental region, where the value of the vertical β function is small compared to the horizontal one.

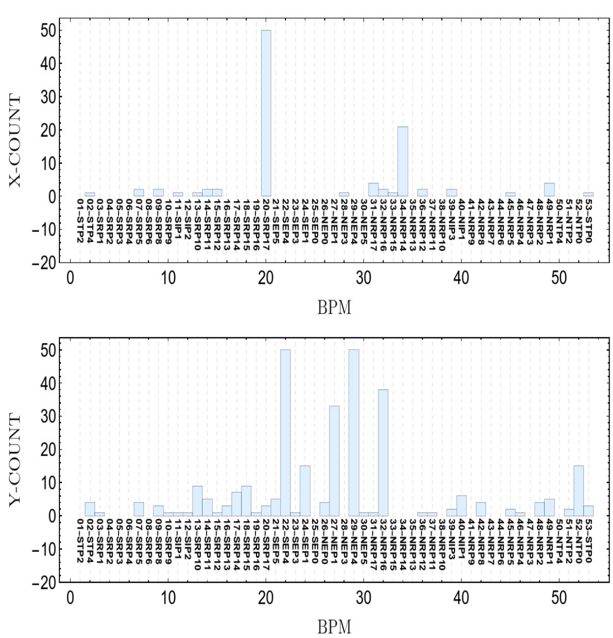

Figure 5: Flagged BPMs for 50 successive measurements. BPMs with high counts correspond to systematic anomalies.

CONCLUSION

The anomaly detection procedure for BPM signals processing at the VEPP-4M was extended. Several methods based on derived features of samples generated from BPM signals were tested. These features along with their robust dispersion estimation have allowed to define anomaly score for BPM signals and to estimate the contamination rate of a given TbT measurement. In combination with unsupervised ML methods, this procedure provides reliable detection of anomalies. An experimental study of anomalies in BPM signals at the VEPP-4M was performed. It was found spike anomalies appear in about 1 % of the signals in a single measurement. Several BPMs were systematically flagged due to different operation conditions. Further improvement and a more detailed study of anomalies are planned in the new season.

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