BPM SYSTEM EVALUATION USING MODEL-INDEPENDENT ANALYSIS*

Chun-xi Wang†, Michael Borland, Vadim Sajaev, Kwang-Je Kim
Advanced Photon Source, Argonne National Laboratory, Argonne, IL

Abstract

An effort is underway at the Advanced Photon Source (APS) to explore the Model-Independent Analysis method on the APS storage ring. Effective methods are developed to efficiently evaluate the beam position monitors' (BPMs') performance and to easily identify the malfunctioning BPMs. Such a monitoring procedure can help to improve the overall reliability and performance of the BPMs, and thus benefit machine operation and physics studies. We show that the Model-Independent Analysis can resolve beam motion below the individual BPM resolution.

1 INTRODUCTION

Statistical analysis of beam position monitor (BPM) data has shown remarkable potential to significantly enhance measurement capability [1, 2]. Motivated by exploiting such potential, various techniques for beam and machine measurements are being developed under the name "Model-Independent Analysis" (MIA). An effort is underway at the Advanced Photon Source (APS) to apply/study MIA to/on the APS storage ring. A basic requirement of MIA is a BPM system that can measure beam positions simultaneously at all BPMs for a large number of turns. For both MIA and other applications, it is important to understand and characterize the performance of a BPM system. Therefore, we are developing MIA-based techniques to systematically and efficiently evaluate the performance of a BPM system. Preliminary results are reported.

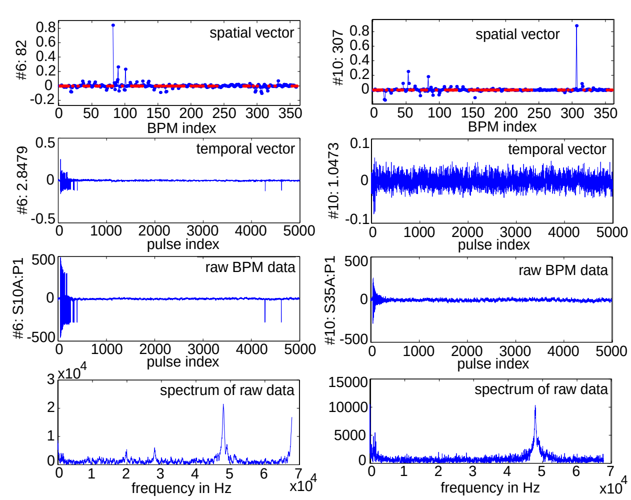
2 ANALYZING BPM PERFORMANCE

The beam history modules in the APS operating system are used to collect (in x-y toggling mode) beam positions of 8192 turns at 360 BPMs for each data set. Horizontal and vertical kickers could be used to excite betatron oscillations. Early design problems in the BPM history module have resulted in significant data corruption. Careful analysis must be done for each data set in order to choose the BPM history modules that are functioning. Although the problems revealed in our analysis are caused by the beam history module instead of other BPM hardware, we will use the generic term BPM without further clarification.

2.1 *Identifying Malfunctioning BPMs*

Most of the malfunctioning BPMs can be identified by visually examining their beam history plots. However, it is a tedious exercise because of the large number of BPMs. To facilitate this process, one of the basic MIA technique, SVD mode analysis, can be used. Let $B_{P\times M}$, P pulses and M BPMs, be the data matrix containing the beam history as its columns. Singular value decomposition (SVD) yields $B = USV^T$, where $S = \mathrm{diag}(s_1, s_2, \cdots, s_M)$ contains the singular values of each mode, $U = [\mathbf{u}_1, \mathbf{u}_2, \cdots, \mathbf{u}_M]$ contains the temporal eigenvector $\mathbf{u}$'s, and $V = [\mathbf{v}_1, \mathbf{v}_2, \cdots, \mathbf{v}_M]$ contains the spatial eigenvector $\mathbf{v}$'s. Because the vectors are normalized to one, a peak value close to one in a v-vector means that the mode is attributable to that peaked BPM. Thus, the potential malfunctioning BPMs can be located simply by examining the maximum values of the v-vectors. We typically use 0.7 as the threshold for selecting potential malfunctioning BPMs. This procedure yields a much smaller number of BPMs for closer examination. For each potential BPM, the corresponding v-vector, u-vector, raw BPM data, and its Fourier spectrum are automatically plotted for visual examination. Using this method, the malfunctioning BPMs can be effectively identified and removed. Many malfunctioning BPMs are found in our data sets. Figure 1 (a) shows an example of a bad BPM and (b) shows another example that represents noisy BPMs picked out by this method. In (b), the BPM history and its spectrum appear normal, but its rms noise is clearly much larger. BPMs are also picked out for various other reasons (e.g., synchronization problem discussed later), and sometimes for no clear reason at all. That is why we would like to visually examine the BPMs picked by the SVD analysis instead of automatically rejecting them.

The SVD analysis, by its nature, is not effective for identifying BPMs that do not respond to beam motion. To solve this problem, the amplitude of betatron oscillation



(a) a bad horizontal BPM (b) a noisy horizontal BPM

Figure 1: Examples of BPMs picked out by SVD analysis.

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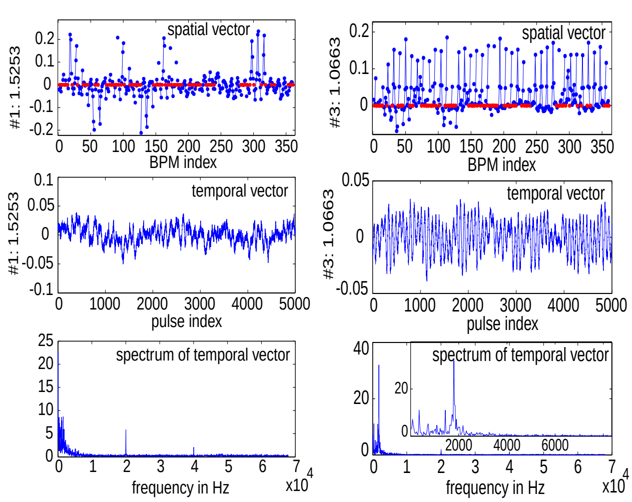
† Wangcx@aps.anl.gov

(other beam motion can be used as well) is automatically estimated at each BPM. Those that have suspiciously low amplitudes are also picked out as potential malfunctioning BPMs. This method has proven to be very effective.

Because some malfunctioning BPMs may occasionally be missed during the analysis because of (accidental) correlation with other malfunctioning BPMs, it is helpful to repeat the procedure a few times as the malfunctioning BPMs are being removed. One may also repeat this procedure over a particularly interesting subset of the recorded beam histories for better scrutiny.

2.2 *Measuring BPM Resolutions*

After identifying and removing the malfunctioning BPMs, we measure the BPM resolutions and estimate the noise floor of the BPM system. For this purpose, we use beam histories that represent an unperturbed beam. Ideally, for each BPM, only random noise exists, and the standard deviation of the noise gives the resolution of the BPM. However, certain systematic noise often exists for various reasons. For example, the beam may not be completely quiet. SVD analysis can be used again to separate the coherent systematic noise from the random noise. Fig. 2 plots the first and third modes of one data set. The second mode is similar to the first, and the other modes appear to be more or less random noise. The first mode (a) shows sporadic motion with a broad-band noise at low frequencies and sharp signals at about 20 and 40 kHz, which is known as “chopper noise.” The third mode (b) clearly shows a coherent beam motion caused by longitudinal oscillation. Its spatial vector corresponds to the dispersion function, and the spectrum of its temporal vector reveals a dominating signal at synchrotron frequency and harmonics of power-line frequency, which come from the high-voltage DC power supplies in the RF system. This mode is probably due to RF phase jitters. Fully understanding and suppressing these coherent modes is important to improving beam stability but it is not our focus here.



(a) the first mode (b) the third mode

Figure 2: Examples of horizontal coherent modes.

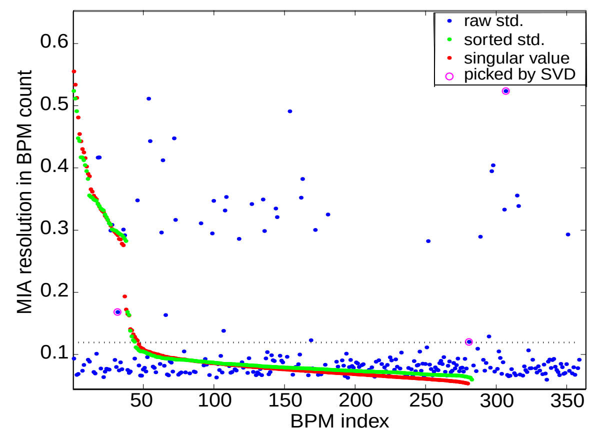


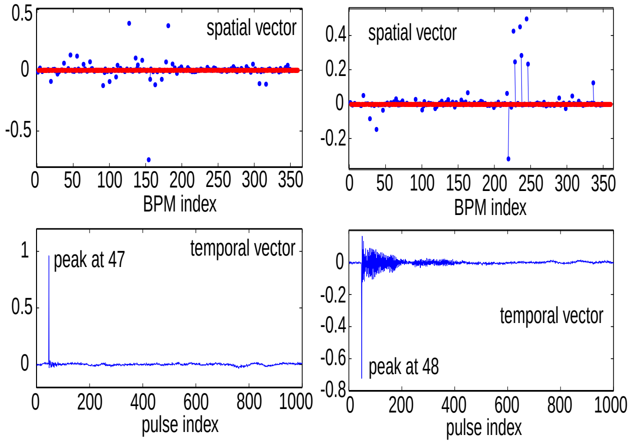
Figure 3: Horizontal BPM resolutions.

To measure the BPM resolutions, we exclude the three coherent modes by zeroing their singular values and reconstructing a data matrix that contains only the random noise. Then we compute the standard deviation of each BPM as its resolution [3]. Fig. 3 shows an automatically generated graph that summarizes the resolutions of a BPM system. There are four sets of data in this graph: 1) the eigenvalues, 2) the standard deviations divided by the square-root of the number of BPMs, 3) the sorted standard deviations to compare with the eigenvalue spectrum, and 4) circles that identify (by SVD) potential malfunctioning BPMs. The agreement between the eigenvalues and the sorted resolutions confirms that we indeed approach the random noise background of the BPM system. These two curves do not reach the total number of BPMs because many BPMs are not functioning and removed.

The BPMs on the upper part of Fig. 3 have much larger noise, mostly because they deliberately use higher gains. The magnitude of the noise floor represents the potential sensitivity of the BPM system for detecting coherent signals. Note that this sensivity is much less than individual BPM resolution (remember the square-root factor). If we remove the noisy BPMs, the BPM system may reach sub-micron resolution (the vertical unit is “BPM count,” $\simeq 7\mu$m, used in our BPM system), provided that all the BPMs function well.

2.3 *Examining BPM Synchronization*

For MIA applications, it is important to have all the BPM readings synchronized on the same pulse. At APS, the BPMs are synchronized only within a couple turns. In any data set, a large percentage of BPMs are unsynchronized, and this happens randomly among BPMs. To examine BPM synchronization, we use a kicked beam as our synchronization signal. Unsynchronized BPMs may generate modes in SVD analysis. Two examples are shown in Fig. 4. The first (a) is a mode due to BPMs that are one turn ahead, and the second (b) is a mode due to BPMs that are one turn behind the kick starting at turn 48. BPMs with larger-than-0.2 magnitudes in the spatial vectors are unsynchronized. Although such modes may be used to identify



(a) one turn ahead (b) one turn behind

Figure 4: Modes due to unsynchronized BPMs.

the unsynchronized BPMs, a more straightforward and effective method is to directly check the starting turn in each BPM. One subtle problem is that some BPMs may not see the kick right away because of $n\pi$ phase advance between the kicker and the BPMs. We are exploring more sophisticated algorithms to automatically detect the unsynchronized BPMs and correct the BPM data by lining up the beam histories. Even if such correction can be done, it still requires a relatively strong synchronization signal and may limit the capability for resolving weak signals.

2.4 Statistics of BPM Performance

Usually, turn-by-turn BPM data are vulnerable to accidental noise. The above techniques can be used to identify malfunctioning BPMs and improve the quality of a given data set. For improving a BPM system, it is more useful to obtain the statistics of BPM performance. A MATLAB routine is being developed to automatically extract this information from available data sets in which BPM performance has been analyzed and recorded.

3 ENHANCING THE ACCURACY OF BEAM OBSERVATION

We have discussed MIA techniques to evaluate BPMs' performance and extract a subset of a recorded BPM data set such that all the BPMs are functioning. This is just a first step for various MIA applications. For a good BPM system, this first step is merely an assurance of data reliability. The next major and common step is to statistically reduce random noise in a data set, which is a signature of MIA. Two examples are shown here to demonstrate one benefit of MIA. Fig. 5 plots the raw digitized history of a horizontally kicked beam recorded at one BPM and the same history after SVD noise reduction. The inserts are two blow-ups. Fig. 6 is a similar plot for a vertically kicked beam. In this case, in addition to the SVD noise reduction, a high-pass Fourier filter is also used to remove the low-frequency noise. The apparent beating pattern is because

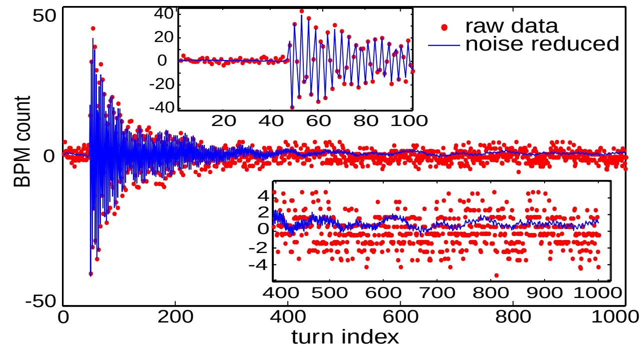


Figure 5: Noise reduction for a horizontally kicked beam.

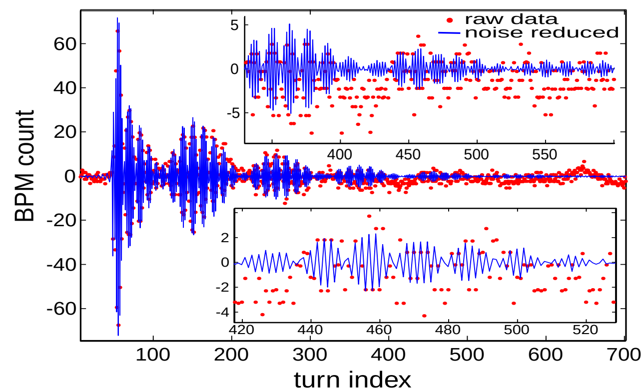


Figure 6: Noise reduction for a vertically kicked beam.

our sampling rate (twice that of the betatron tune 0.27 in x-y toggling mode) is close to half integer. In both cases, even though we still suffer from unsynchronized BPMs, the benefit is obvious. Beam motion can be clearly seen beyond the gridlines of BPM digitization.

4 SUMMARY

Although preliminary, our work demonstrates that MIA techniques can be used to systematically evaluate the performance of a BPM system. Such information is useful for monitoring and improving the quality of BPMs, which is important not only for MIA but also for other applications such as feedback control and physics studies. Our discussions are focused on a turn-by-turn BPM system. The same analysis should be useful for systems based on averaged orbits.

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5 REFERENCES

[1] J. Irwin, C.X. Wang, Y. Yan, et. al., *Phys. Rev. Lett.* **82**(8), 1684 (1999).

[2] Chun-xi Wang, *Model Independent Analysis of beam centroid dynamics in accelerators*, Ph.D. dissertation, Stanford University.

[3] Steve Smith, private communication. To some extent, Smith at SLAC used similar techniques to estimate BPM resolutions before MIA was established.