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HIGH-ACCURACY DIAGNOSTIC TOOL FOR BEAM POSITION MONITOR TROUBLESHOOTING IN SSRF BASED ON CLUSTERING ANALYSIS *

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Abstract

Beam position monitors (BPMs) are important to monitor the beam moving steadily. In spite of some data is viewed and analysed, a large fraction of data has never been effectively analysed in accelerator operation. It lead to some useful information not coming to the surface during the beam position monitor troubleshooting processing.

We will describe in this paper our efforts to use clustering analysis techniques to pull out new information from existing beam data. Our focus has been to look at malfunction of BPM, associating basic running data that is β oscillation of X and Y directions, energy oscillation and doing predictive analysis. Clustering analysis results showed that 140 BPMs could be classified into normal group and fault group and abnormal BPM could be separated. Based on the results, the algorithm could locate fault BPM and it could be an effective supplement for data analysis in accelerator physics.

INTRODUCTION

The storage ring in SSRF is equipped with 140 BPMs located at 20 cells of the storage ring to monitor the beam dynamics[1] . Each one can give a specific signal that can indicate some properties of the beams at its position individually. Usually, these BPMs are used to inform the accelerator physicists and operators the local status of the beams, such as the beam position and (relative) beam current or lifetime. Meanwhile, the BPM also serve as the orbit feedback system to ensure stability of the beam dynamics[2]. Comparing the measured and computed values of the beam dynamics at each position, one can tell how well the state of runtime accelerator. It could literally see that the BPMs are the eyes and ears for the SSRF. However, a typical BPM system consists of the probe (button-type or stripline-type), electronics (Libra Electronics/ Brilliance in SSRF) and transferring component (cables and such), and complex composition parts easily lead lots of failure. Ever since the SSRF commissioning in 2009, the BPM have occurred all kinds of malfunction. They were permanently damage of individual probe or corresponding cable, misaligned (position/angle) probes, high-frequency vibrations, electronics noise, and others. These faults mean useless of the signals from the BPM and seriously affect the light source supply time. Hence, it is essential to find an effective tool to detect the faulty BPM for operation of the storage ring.

In our study, we put much effort into real-time processing of data, in order to present to operators results that allow them to either diagnose the health of the system or have a signal on which to perform some optimization process. With development in machine learning methods, a series of powerful analysis approaches make it possible for detecting beam position monitor's stability. Cluster analysis is one of machine learning methods. It is aimed at classifying elements into categories on the basis of their similarity[3]. Its applications range from astronomy to bioinformatics, bibliometric, and pattern recognition. Clustering by fast search and find of density peaks is a new approach based on the idea that cluster centres are characterized by a higher density than their neighbours and by a relatively large distance from points with higher densities[4]. This idea forms the basis of a clustering procedure in which the number of clusters arises intuitively, outliers are automatically spotted and excluded from the analysis. It is able to detect non-spherical clusters and automatically find the correct number of clusters. Based on the advantage of clustering by fast search and find of density peaks, this study establish a multi-dimensional clustering analysis model and monitor the running status of accelerator malfunction.

EXPERIMENTAL DATA AND ANALYSIS METHOD

In this study, the experimental data were collected from the BPM turn-by-turn (TBT) data under the different beam intensity, respectively, are 69 mA 73 mA 78 mA 88 mA 90 mA 96 mA 100mA 104mA 108 mA 111 mA 115 mA 120 mA 124 mA 130 mA 134 mA 140 mA 144 mA 157 mA. By analysing the raw data, we extracted the data of transverse oscillation of X and Y direction, energy oscillation data to judge the faulty BPM. A multi-dimensional clustering analysis model was established and the three characteristic factors were the iuput variables to locate the BPM malfunctions at different beam intensity. The model has a assumptions that cluster centres are surrounded by neighbours with lower local density and that they are at a relatively large distance from any points with a higher local density. For each data point i, it will compute two quantities: its local density ρi and its distance δi from points of higher density. Both these quantities depend only on the distances dij between data points, which are assumed to satisfy the triangular inequality. The local density ρi of data point i is defined as

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$$\rho_i = \sum_j \chi(d_{ij} - d_c) \qquad (1)$$

where χ (x) =1 if x < 0 and χ (x)=0 otherwise, and dc is a cutoff distance. Basically, ρi is equal to the number of points that are closer than dc to point i. The algorithm is sensitive only to the relative magnitude of ρi in different points, implying that, for large data sets, the results of the analysis are robust with respect to the choice of dc. In this paper, the dc is 0.02. On the other hand, δi is measured by computing the minimum distance between the point i and any other point with higher density:

$$\delta_i = \min_{j:\rho_j > \rho_i} (d_{ij}) \qquad (2)$$

For the point with highest density, we conventionally take $\delta_i = \max_j (d_{ij})$. Note that δi is much larger than the typical nearest neighbour distance only for points that are local or global maxima in the density. Thus, cluster centres are recognized as points for which the value of δi is anomalously large. Generally, the value of δi and ρi represent whether the point is cluster centre, the typical characteristic of cluster centre is the value of δi and ρi are larger. Decision graph could depict the value of δi and ρi and show which points are cluster centre.

RESULTS AND DISCUSSION

In the data processing, the BPM signals are the average of 140 ID* 2048 turns at different beam intensity. Figure 1 showed that the analysis result under the 157 mA beam intensity. Theoretically, the farther away the reference value 1, the more easily faulty of BPMs. 75# and 68# BPMs could be the malfunction of BPMs, because they are far away the reference value 1.

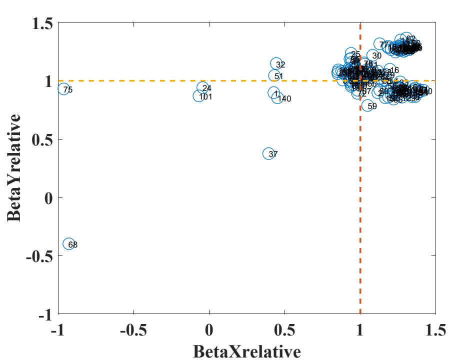

Figure 1: Scatter diagram of cluster analysis based on transverse oscillation of X and Y direction.

Meanwhile, it could see that the all BPMs could be classified three categories from the scatter diagram. In order to verify the observation results, we calculate the decision graph is showed in Figure 2. Theoretically, faulty BPMs corresponds to the smaller ρ and the larger δ , cluster cores mean the larger ρ and the larger δ[5]. So it could be drawed a conclusion that 75# and 68# are faulty BPMs and the 127#,105# and 47# BPMs represents three cluster cores. In order to find out which BPM belongs to one of the three categories, the model give answer and Fig.3 shows the clustering results of all BPMs.

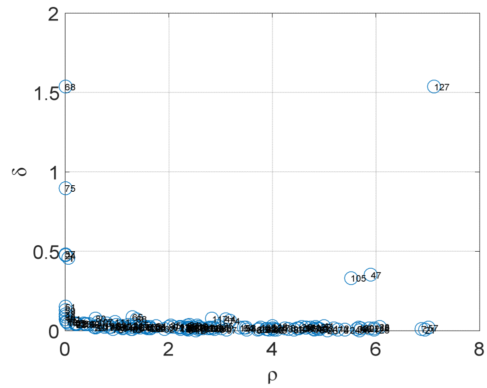

Figure 2: Decision graph.

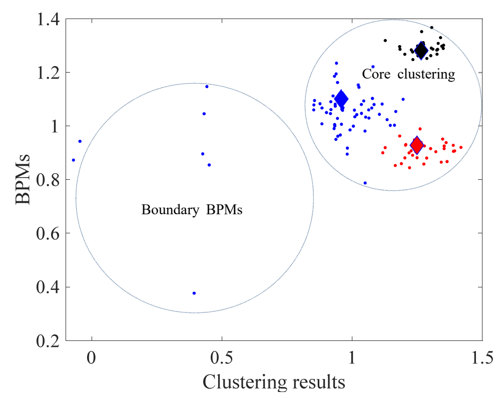

Figure 3: Clustering results for all BPMs.

The clustering results with respect to all BPM are shown in Figure 3. From the clustering results, 140 BPMs can be classified into three normal group and boundary BPMs. And that, the abnormal BPMs are filtered out in Figure 3. According to the absence number, we can find the abnormal BPMs are 68# and 75#.

To ensure the accuracy of clustering results, the input variables increase to three for the multi-dimensional clustering analysis model. They are, respectively, transverse oscillation of X and Y direction and energy oscillation. The result is shown in Figure 4.

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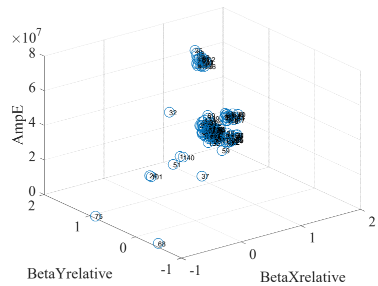

Figure 4: Scatter diagram based on transverse oscillation of X , Y direction and energy oscillation.

Based on the multi-dimensional clustering analysis model, the research results showed that no matter the input variables are two or three, the faulty BPMs are both 68# and 75#. It illustrated that the faulty BPMs are not sensitive to the beam characteristic, so we can be sure that they are faulty. The analysis results are shown in the Table 1.

Table 1: The Analysis Results of Cluster Analysis

BI/mA	Faulty BPMs		Cluster Cores		
157mA	68#	75#	47#	105#	127#
144 mA	68#	75#	108#	118#	119#
140 mA	68#	75#	42#	38#	105#
134 mA	68#	75#	70#	91#	47#
130 mA	68#	75#	76#	78#	110#
124 mA	68#	75#	40#	77#	97#
120 mA	68#	75#	47#	49#	70#
115 mA	68#	75#	53#	110#	126#
111 mA	68#	75#	5#	6#	133#
108 mA	68#	75#	6#	47#	57#
104 mA	68#	75#	5#	8#	71#
100 mA	68#	75#	29#	73#	83#
96 mA	68#	75#	29#	31#	106#
90 mA	68#	75#	26#	126#	
88 mA	68#	75#	26#	29#	118#
78 mA	68#	75#	8#	53#	89#
73 mA	68#	75#	35#	38#	126#
69 mA	68#	75#	57#	106#	122#

The result demonstrates the faulty BPMs can be detected and the multi-dimensional clustering analysis model could classify beam data into different clusters on the basis of their similarity. But each BPM belonging to the clusters is different that depends on the beam intensity. The cluster distribution result of 1# BPM is shown in Figure 5. Which cluster core it belonging to depends on the experiment data, no matter which category it is, it's normal BPM. The cluster distribution result of all BPM is shown in Fig. 6 (not include 68# and 75# BPM).

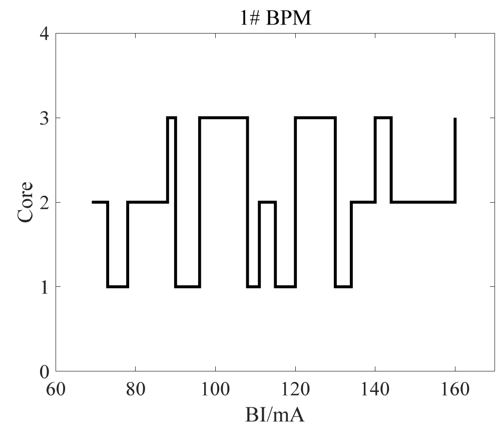

Figure 5: Cluster distribution of 1# BPM.

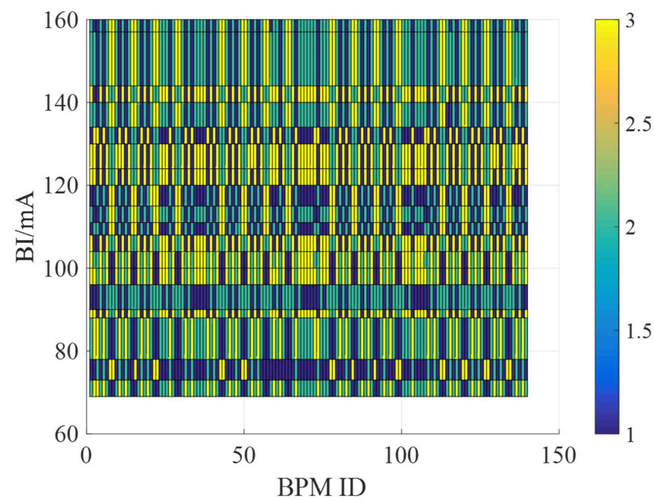

Figure 6: Cluster distribution of each BPM.

CONCLUSION

As the key beam diagnostics tool, BPM systems are widely equipped in all kinds of accelerators and are being used in daily operation and machine study. To better ensure the operation of the light source, a proper method detecting faulty beam position monitor or monitoring their stability is essential. This study proposed a multi-dimensional clustering analysis model to search faulty BPMs.

The experimental results demonstrate that 68# and 75# BPM are faulty, the other BPMs could be classified three categories. Whether the three categories belong to one big category, it needs to further study. In short, the proposed method could capture the faulty BPMs and would be meaningful in the field of beam diagnosis.

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