Automatic Channel Fault Detection and Diagnosis System for a Small Animal APD-Based Digital PET Scanner

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Abstract—Fault detection and diagnosis is critical to many applications in order to ensure proper operation and performance over time. Positron emission tomography (PET) systems that require regular calibrations by qualified scanner operators are good candidates for such continuous improvements. Furthermore, for scanners employing one-to-one coupling of crystals to photodetectors to achieve enhanced spatial resolution and contrast, the calibration task is even more daunting because of the large number of independent channels involved. To cope with the additional complexity of the calibration and quality control procedures of these scanners, an intelligent system (IS) was designed to perform fault detection and diagnosis (FDD) of malfunctioning channels. The IS can be broken down into four hierarchical modules: parameter extraction, channel fault detection, fault prioritization and diagnosis. Of these modules, the first two have previously been reported and this paper focuses on fault prioritization and diagnosis. The purpose of the fault prioritization module is to help the operator to zero in on the faults that need immediate attention. The fault diagnosis module will then identify the causes of the malfunction and propose an explanation of the reasons that lead to the diagnosis. The FDD system was implemented on a LabPET™ avalanche photodiode (APD)-based digital PET scanner. Experiments demonstrated a FDD Sensitivity of 99.3% (with a 95% confidence interval (CI) of [98.7, 99.9]) for major faults. Globally, the Balanced Accuracy of the diagnosis for varying fault severities is 92%. This suggests the IS can greatly benefit the operators in their maintenance task.

I. INTRODUCTION

Recent studies have shown the importance of quality control testing (QC) to ensure proper performance of positron emission tomography (PET) scanners [1]. Intelligent fault detection and diagnosis (FDD) systems have demonstrated qualities that meet the requirements for large nuclear experiments [2] and can significantly reduce the workload of QC personnel [3]. Therefore, to minimize the burden of frequent calibration and QC procedures on complex medical imaging devices such as PET scanners, an intelligent system (IS) for channel FDD was proposed [4]. Fault prioritization and diagnosis were missing from the previous work but it is crucial for complete QC testing. Additionally, the proposed IS could not learn from new faults preventing it from adapting to its environment and coping with new types of faults.

This paper proposes a fault prioritization and diagnosis system to support the aforesaided IS for the LabPET™ scanner [5] with the goals of increasing fault detection efficiency, implementing fault prioritization and diagnosis to allow evaluation of the complete IS performance.

II. INTELLIGENT SYSTEM

The proposed IS system consists of 4 adaptable modules (parameter extraction, fault detection, fault prioritization and fault diagnosis) coupled to a knowledge base and a fault history database (Fig. 1). The control panel of LabPET™ scanners provides data to the parameter extraction module, which transforms it to an appropriate format for the channel fault detection module. Then, the channel fault detection module generates a list of faulty channels that are afterwards sorted by the fault prioritization module. Finally, the fault diagnosis module produces a diagnosis for every channel in the fault list. The IS uses a knowledge base and a fault history database as prior information of the LabPET™ scanner.

A. Fault Prioritization

The purpose of the fault prioritization module is to help the operators to zero in on the faults needing immediate attention (Fig. 2). To do this, the module ranks the detected channel faults by a priority indicator determined from available data on individual channels. Since groups of nearby failed channels have a higher tendency of causing artifacts in reconstructed images, the priority indicator consists of a channel health indicator weighted by a clustering factor adjusted to the failed channel cluster size. The fault prioritization module receives the list of channels to sort from the fault detection module. The priority indicator is then extracted for all channels using fuzzy logic rules from the knowledge base. Clustering is performed by using the density-based spatial clustering of applications...
Intelligent System

Fault prioritization
Parameter extraction
Fault diagnosis
PET scanner control panel
Knowledge base
Channel fault detection
Fault prioritization
Fault history

Fig. 1: The global architecture of the intelligent FDD system features a modular architecture.

Fault priority Indicator extraction
PET scanner control panel
Scanner geometry
Failed channel clustering
Channel cluster size
Failed channels
Indication extraction
Channel priority
Fault history

Fig. 2: The fault prioritization module uses fuzzy logic to extract the priority indicator from the health indicator and the proximity of other failed channels.

with noise (DBSCAN) [6] algorithm, which is adequate in this situation because of the number of fault clusters and shapes. The cluster size is mapped to a fuzzy logic variable with four linguistic terms (SMALL, MEDIUM, LARGE, HUGE) where a huge cluster consists of around 45 failed channels for the LabPET™ system. This value was determined by an experiment where multiple failed channel cluster sizes were simulated, and image quality parameters where extracted from the reconstructed images [7]. A 45 channels cluster was found to reduce significantly the recovery coefficient of 1 mm diameter sources, as well as almost doubling the uniformity percentage standard deviation in the reconstructed image of a uniform flood source. It thus makes it a good reference for a huge cluster term (one that needs immediate attention). The effects of a 45 channels cluster is hard to detect by visual inspection of the image, but Fig. 3 shows the effects on a NEMA image quality phantom with 256 channel failed out of 3072 (Fig. 3b) compared to a reconstruction without these failures (Fig. 3a).

Fig. 3: Reconstruction of a NEMA image quality phantom with 256 channel failed out of 3072 (Fig. 3b) compared to a reconstruction without these failures (Fig. 3a).

B. Fault Diagnosis

The fault diagnosis module produces a diagnosis of the detected faults so that appropriate actions may be undertaken to correct the faults (Fig. 4). To help the operator interpret the diagnosis, it includes the probability of the selected diagnosis and also provides detailed explanations of the reasons leading to the diagnosis. The inputs to this module are PET scanner control panel data, extracted parameters and performance indicators from the fault detection module. They are used to perform 2 types of diagnosis in parallel: a history based diagnosis and a rule based diagnosis. The history based diagnosis module makes use of machine learning techniques and has the capacity to adapt to new types of faults as well as to provide the probability of the diagnosis. It uses an ever expanding fault history database to learn how to perform diagnosis and adapt to the environment. On the other hand, the rule based expert system (ES) diagnosis module makes use of a knowledge base to diagnose and provide detailed explanations of the diagnosis. The results from both the history based diagnosis and the rule based diagnosis are then merged into a complete diagnosis that is presented to the scanner operator. For example, a diagnosis could be: "Increase Polarization (96%): Channel has a calibration problem (channel LYSO photopeak drift is high), channel is weak (strength is low, identification is failed, energy is failed), channel is not saturated and polarization increase is safe.". The merge is a logical OR that ensures the channel diagnosis incorporates the unique parameters of both diagnosis methods.

Machine learning is made by random decision forests [9], which is an ensemble method that uses a multitude of decision trees. Decision trees have historically been used for FDD [10] and random decision forests show improvements over using only one tree. Every node in a decision tree is a question on the input parameters and the branches represent the answers to those questions. The leaves at the bottom of the three indicate the identified diagnosis for the channel being diagnosed. In decision forests, a multitude of trees are generated from training data and the diagnosis of each of the trees are taken into account. In the learning phase, the trees are constructed
Currently, the fault detection threshold is crossed when the probability for a diagnosis reaches 70%.

III. MATERIALS AND METHODS

Experimental measurements were conducted on a 8 cm axial length LabPET-TM scanner at the Sherbrooke Molecular Imaging Center [14]. The LabPET 8 scanner is an avalanche photodiode (APD)-based small animal PET imaging system having 3072 channels. The experiments were carried out in order to:

- Evaluate the correlation of the priority indicator with the severity of faults.
- Evaluate the IS FDD Sensitivity for major faults and the diagnosis hypothesis test Balanced Accuracy for varying fault severities.
- Evaluate the IS FDD Sensitivity for varying fault severities.
- Evaluate the IS severity diagnosis Sensitivity.

All the experiments consisted in introducing fake faults in the acquisition channels of the scanner by modifying APD bias voltage and noise threshold in the scanner configuration file. After the faults were introduced, the required data was taken from the scanner control panel, the IS was used to detect and diagnose the introduced faults and performance metrics were evaluated. Major channel faults were introduced on 800 randomly selected channels by lowering the APD bias voltage by 50 V. Additionally, fault severities were introduced by generating 5 distinct levels of modifications on APD bias voltage and noise threshold (120 channels per level per fault type). APD bias fault levels range from 5-25 V by both positive and negative 5 V increments. Finally, noise threshold fault levels range from 5-25 ADC bins by both positive and negative 5 ADC bins increments.

The experiments were conducted to extract the following performance metrics of the system: channel priority indicator responsiveness, global diagnosis statistics, FDD Sensitivity per severity level, and finally, severity diagnosis Sensitivity.

A. Channel Priority Indicator Responsiveness

As the fault severity increases, the priority indicator should also increase so that the highest severity faults are assigned the highest priority. To test this correlation, the distribution of the priority indicator for each severity was extracted using the results from the introduced fault severities. The Spearman rank correlation between the priority indicator and fault level was also evaluated.

B. Global Diagnosis Statistics

The IS global performance was evaluated using measurements of classification test statistics. The global FDD classification test Sensitivity was evaluated for the major faults. For the experiments, this is evaluated by dividing the number of correct diagnosis by the number of introduced faults:

$$\text{Sensitivity} = \frac{\text{true positives}}{\text{positive conditions}}$$  \hspace{1cm} (1)
The global FDD Specificity was evaluated as the number of correctly identified working channels divided by the number of properly working channels:

\[
\text{Specificity} = \frac{\text{true negatives}}{\text{negative conditions}} \quad (2)
\]

The Balanced Accuracy is the mean of Sensitivity (Eq. 1) and Specificity (Eq. 2) and it was also evaluated because Sensitivity only accounts for the modified channels (positive conditions). Since, the plain Accuracy can conduct to inflating estimates due to the moderate class imbalance in the test data as there are significantly less faults than working channels, the Balanced Accuracy was used.

\[
\text{Balanced Accuracy} = \frac{\text{Sensitivity} + \text{Specificity}}{2} \quad (3)
\]

C. FDD Sensitivity Per Severity Level

The FDD Sensitivity was evaluated for each fault severity and for APD bias voltage modifications as well as noise threshold modifications. As before, this is evaluated by dividing the number of correct diagnosis for a severity and fault type by the number of introduced faults of the specified severity and fault type. This should help determine what types of faults are harder to diagnose and should also result in an indication of the IS responsiveness.

D. Severity Diagnosis Sensitivity

In addition to providing the faults causes, the system can also be used to diagnose the faults severities. This is very useful for scanner operators since the fault severity can guide the magnitude of the correction that is to be applied in order to correct a fault. The severity diagnosis Sensitivity (Eq. 1) can be evaluated by dividing the number of correctly diagnosed severities for a fault type by the number correctly diagnosed faults of the same type.

IV. RESULTS

A. Channel Priority Indicator Responsiveness

The distribution of the priority indicator for each fault severity is shown in boxplots (Figs. 5 and 6). Boxplots better represent non Gaussian statistical distributions; they provide a good overview of non parametric distributions. In these plots, boxes show the interquartile range (IQR) and outliers where identified when data points are farther than 1.5 IQR from the median. The “Ref” label corresponds to the distribution of the priority indicator before the introduction of faults.

B. Global Diagnosis Statistics

The measured FDD Sensitivity for major faults (50 V APD bias decrease), which corresponds to the classification test Sensitivity, is 99.3 % (CI: [98.7, 99.9]). The global diagnosis test Balanced Accuracy results for all introduced faults are shown in Table I. It is important to keep in mind that a system randomly choosing a diagnosis would result in an Accuracy of 50 %. At first glance, the IS global Balanced Accuracy remains fairly high irrespective of the fault type.

C. FDD Sensitivity Per Severity Level

The FDD sensitivities for varying fault severities are shown in Fig. 7 for APD bias voltage modifications and Fig. 8 for
TABLE I: Global Diagnosis Test Balanced Accuracy

| HV Bias | Noise threshold |
|---------|-----------------|
| Increase| Decrease        |
| Increase| Decrease        | Globally |
| 95 %    | 87 %            | 91 %     | 88 %     | 92 % |

noise threshold modifications. As expected, FDD Sensitivity increases rapidly with fault severity. There is a slight drop in FDD Sensitivity for the last level for both fault types, an hypothesis for this observation will be provided in the discussion section.

Fig. 7: FDD Sensitivity for increasing APD bias fault severities.

Fig. 8: FDD Sensitivity for increasing noise threshold fault severities.

D. Severity Diagnosis Sensitivity

Finally, the severity diagnosis is evaluated for different severities as shown in Figs. 9 and 10. The error bars are larger than for FDD Sensitivity since the severity diagnosis Sensitivity only takes into account the channels that had a correct diagnosis.

Fig. 9: Severity diagnosis Sensitivity for increasing APD bias fault severities.

Fig. 10: Severity diagnosis Sensitivity for increasing noise threshold fault severities.

V. DISCUSSION

There is a good correlation between the priority indicator and fault severity, which confirms that the indicator can be used to prioritize fault correction in the scanner. The global FDD Sensitivity of the system is excellent for major faults (50 V) and fair for different fault levels. Severity diagnosis Sensitivity is good and should be indicated to the scanner operators as it can help them determine the degree of the configuration modifications to apply. The Accuracy is acceptable even if some errors are to be expected, but it is worth mentioning that as the fault history expands, the results will
likely improve. The results show that lower fault severities are not diagnosed reliably, but an important factor to consider is that lower levels of configuration change do not insure that faults are actually created and that they have any significant effect on image quality. Further investigation will be required to improve the robustness of the IS for mild to medium severity faults in the system.

An unexpected drop in FDD Sensitivity for the last level for both fault types was observed. This will need to be investigated further, but our hypothesis is that this level of fault triggers more changes in the channel performance indicators, which are used by the fault diagnosis module to determine the fault diagnosis probability making multiple diagnosis plausible (higher probabilities). Currently, faults are detected when the probability for a diagnosis reaches 70%, so if two different diagnosis are plausible, even though one is higher than the other, this could lead to a missed detection. For major faults this situation seems to no longer apply as seen by the FDD Sensitivity rate.

VI. CONCLUSION

The fault prioritization and diagnosis modules of an intelligent system (IS) designed to perform channel fault detection and diagnosis (FDD) was proposed for the LabPET™ scanner. The modules were evaluated and have shown a FDD Sensitivity of 99.3% (CI: [98.7, 99.9]) for major faults and a Balanced Accuracy of 92% for varying fault severities. The priority indicator correlates well to channel fault severity, which indicates that the system will be able to sort faults effectively. The performance of the diagnosis module indicates that the IS is capable of diagnosing many faults automatically and is suitable for use in the field. Finally, the IS will continue to be investigated to improve performance and help reduce the burden of the quality control (QC) procedures for scanner operators.

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