Digital Pulse Shape Discrimination of Detector Data using Fuzzy Clustering

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Introduction

In accelerator based experiments, data acquisition is done by CAMAC, VME and other systems. The current trend is to digitize the pulse shapes and not just the peak heights of all the input channels, by means of Flash ADCs. In view of the large number of channels involved, this leads to unprecedented data volumes. Therefore, attempts to perform a first level of analysis in real time using algorithms implemented in FPGA have become important.

In the present work, digital pulse shape discrimination using Fuzzy clustering has been investigated. The attempt has been to devise general purpose PSD Techniques, loosely coupled with the characteristics of detector or particle type, for particle identification. The method is applicable to neutron-gamma discrimination for liquid scintillators and charged particles detected by Si detectors.

PSD using Fuzzy Clustering

Fuzzy-C-Means (FCM) algorithm [1] can be applied to a set of digitized signals in order to find cluster centroids, which are characteristic signature of a particle type. The number of different particle types present in the data set must be known a priori.

FCM is a data clustering technique in which a data set is grouped into 'n' clusters with every data point in the data set belonging to every cluster to some degree, which is specified by a membership grade. If the similarity of two points x and y is expressed by some norm ||x-y||, the aim of the FCM algorithm is to minimize the total intra-class distance defined by

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} \| x_i - c_j \|^2$$

where N is the number of data points, C is the number of assumed centroids, and u_{ij} are the elements of the membership matrix expressing the degree of membership of data point x_i to the centroid c_j. The parameter 'm' quantifies the fuzziness of the method. The minimization of J_m has to be performed with the constraints

$$u_{ij} \in [0,1], \quad \sum_{j=1}^{C} u_{ij} = 1, \quad \sum_{i=1}^{N} u_{ij} > 0, \quad \forall i,j$$

which leads to an iterative solution by calculating in each step the centroid as

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} \cdot x_i}{\sum_{i}^{N} u_{ij}^{m}}$$

and memberships as

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\| x_i - c_j \|}{\| x_i - c_k \|} \right)^{2/(m-1)}}$$

until a termination criterion is met. In this way J_m converges to a local minimum. After the algorithm converges, the particle identification can be carried out by using a custom selection rule based on membership grades. The other method to determine particle type is by calculating the Manhattan distance of individual pulses to the cluster centroids.

Analysis Methodology

The fuzzy analysis was carried out on two distinct sets of data, viz., simulated Neutron-Gamma pulses and experimentally obtained α-^{7}Li pulses.

Simulated Neutron and Gamma pulses were generated using a C program, by using the empirical formula given by the Marrone's model [2]. To completely emulate the experimental pulses, Gaussian noise ranging from 15dB to 40dB, was introduced in ideal neutron and gamma pulses. α-^{7}Li digital data was acquired from the ^{7}Li+^{89}Y at 25 MeV beam energy experiment done at BARC-TIFR Pelletron, Mumbai. Silicon detector was used to detect particles obtained during the experiments.

The experimentally obtained data was subjected to preprocessing to make it amenable to Fuzzy analysis. 25 points moving average algorithm was applied twice to remove the high frequency noise present in the data set. The signals, devoid of high frequency noise, were subjected to amplitude alignment through normalization so that they fall within the same amplitude range. Further, time alignment of signals was achieved through the application of digital constant fraction timing method [3]. The simulated neutron-gamma data set required no treatment, save for the application of moving average filter.

FCM analysis was performed on a detector pulse data set, in which individual pulses had already been classified, on the basis of rise time information, by laborious manual inspection, either as α or ^{7}Li. For the experimentally obtained data, α pulse had high rise-time, in range of 8.72µs - 9.09µs, as compared to the Li pulse, which had rise time in the range of 13.550µs – 13.938µs.

FCM was input a detector pulse data set whose individual pulse identity was known a priori. The measurement of particle identification capabilities of FCM on the charged particle data was based on, how well the prediction matched with the expected sequence of pulses.

Results

For the simulated neutron-gamma pulses, FCM algorithm shows excellent particle identification at 24dB SNR and above. Below 24 dB SNR, the noise component becomes predominant and pulse identification using, both, membership grade and distance method fail. This can also be attributed to the significant departure of characteristic Gamma-Neutron pulse profile, obtained through FCM, from averaged normalized Gamma-Neutron pulse.

The results for α-^{7}Li data set were in complete conformance with the expected sequence of pulses. Fig. 1 shows how the membership value for 22 sample pulses clearly separates out into 2 groups, with values clustered close to 1(alpha) and 0(lithium).

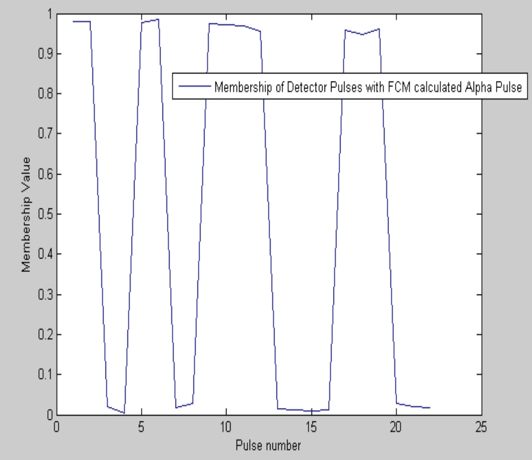

Fig. 1 Membership grade with FCM calculated α pulse profile. Degree of membership >0.9 denote an α pulse.

Conclusion

The suitability of utilizing fuzzy clustering, using FCM algorithm, for particle identification has been completed for simulated Neutron-Gamma pulses and experimental α-^{7}Li pulses data set. The results have convincingly proven that FCM, inter alia, can be used for characteristic pulse determination of a particular type. The pulse profile obtained through FCM, characteristic signature of a particle type, is used as a reference during the identification of pulses.

The methodologies for particle identification, used in the current work, viz., membership grade method and distance method, are exceedingly simple and fast. This opens up the door for online PSD by FPGA implementation of described approaches.

References

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