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Intelligent Surveillance System Based on the Self-organized Feature Mapping and RGB Color Plane Threshold Approach

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Abstract

After about 10 years of technology development and closer international cooperation with the US, AECL and the IAEA, DUPIC project has come to the point where hot material was introduced in the DUPIC process and has been in normal use. DUPIC safeguards program has been conducted to support DUPIC fuel development study from the earliest stage of the research. The major safeguards technology involved here is to design and fabricate a neutron coincidence counting system for process accountability, and also an unattended continuous surveillance system. Unattended continuous surveillance systems result in large amounts of data, which require much time and effort to inspect. Therefore, it is necessary to develop software that automatically pinpoints and diagnoses the anomalies from the data. In this regard, this paper presents a novel concept of a continuous surveillance system that integrates visual surveillance and NDA data by the use of a neural networks based on the self-organized feature mapping. The integral part of the multi-sensory system and analytical paradigm may provide an effective technological alternative for safeguarding of high-level radioactive material handling facilities.

1. Introduction

The DUPIC study is an effort of looking into fuel cycle technology that would be implicated with international non-proliferation policy in using plutonium bearing spent nuclear fuels. Subsequently, with a favorable international consensus, the DUPIC project could go on with the feasibility study on several options of the DUPIC process and its safeguardability. Since then, a comprehensive research and development program is being implemented at KAERI to demonstrate the DUPIC fuel cycle concept. After about 10 years of technology development and closer international cooperation with the US, AECL and the IAEA, DUPIC project has come to the point where hot material was introduced in the DUPIC process and has been in normal use.

A safeguards system has been developed in the course of supporting a fuel cycle process to fabricate DUPIC fuel[1]. The major safeguards technology involved here was to design and fabricate a neutron coincidence counting system for process accountability, and also an unattended continuous monitoring system in association with independent verification by the IAEA. This combined technology is to produce information of nuclear material content and to maintain knowledge of the continuity of nuclear material flow. In addition to hardware development, diagnosis software has been developed to assist data acquisition, data review, and data evaluation based on artificial intelligence[2].

The safeguards requirement for verifiably uninterrupted surveillance has remained largely unchanged for a long time. However, the required implementation has changed dramatically in recent years. The need for cryptographic authentication, motion detection, interaction with other sensors and instruments, and the anticipated demand for object recognition have placed ever-increasing demands on the computational performance and operational capabilities of the surveillance systems[3]. Surveillance systems, therefore, used in spent nuclear fuel handling facility have a potential to generate large amount of data and interpreting data from the systems is a tedious and time-consuming task. It typically requires the examination of large amounts of data for unusual patterns of activity, and because of the complexity and diversity of the data, a new advanced approaches are needed to analyze the information gathered from process monitors so that humans can direct their attention to possible problems.

This paper discusses the design and testing of the intelligent data analysis system for SNM (Significant Nuclear Material) monitoring and surveillance applications for DFDF (DUPIC Fuel Development Facility). The prototype system builds upon the data acquisition hardware and software within the DFDF and incorporates innovative data analysis techniques of neural networks. The architecture for the surveillance system is described in the next section. Descriptions of the DUPIC surveillance system configuration and the initial software module follow. Preliminary results of module testing are presented along with an outline of ongoing module development and system integration activities.

2. System Configuration

The major goal for the R&D works in the C/S (Containment and Surveillance) system is focused on providing unattended continuous monitoring of the spent fuel transportation at the reception area of the DUPIC facility. In the system development, particular efforts have been made for digital analysis of events by incorporating an advanced diagnosis mechanism to selectively draw a conclusion on the significant events throughout the monitoring period. Several technical approaches have been adopted to develop the C/S system based on integrating the video and radiation sensors in a common time dimension through image processing and analyzing the integrated data by artificial intelligence. The key design characteristics of the intelligent C/S system could be summarized as follows.

- On-line integration of video and radiation signal, and data processing:

The C/S system adopted image-processing techniques to identify foreign objects entering the safeguarded region. The program also entails detailed geometric analysis to characterize the objects, e.g. whether the object is a fuel transport cask or human workers. A series of image processing is performed and collected over moving time window then results in temporal behavioral features from the video data. This technique facilitates effective integration of the spatial video data with other temporal sensor signals. Prototypical implementation is also made for the online integration of video signal with radiation data that are obtained through actual experimental spent fuel transport experiments.

- Diagnosis of safeguards events using an artificial neural intelligence:

Intelligent data analysis software has been developed to review the integrated sensor signals automatically and diagnoses anomalies of the activities. This diagnosis also entails detailed characterization of the material transport events. Central to this diagnosis system is an ANN (artificial neural networks), which takes characteristic features extracted from the

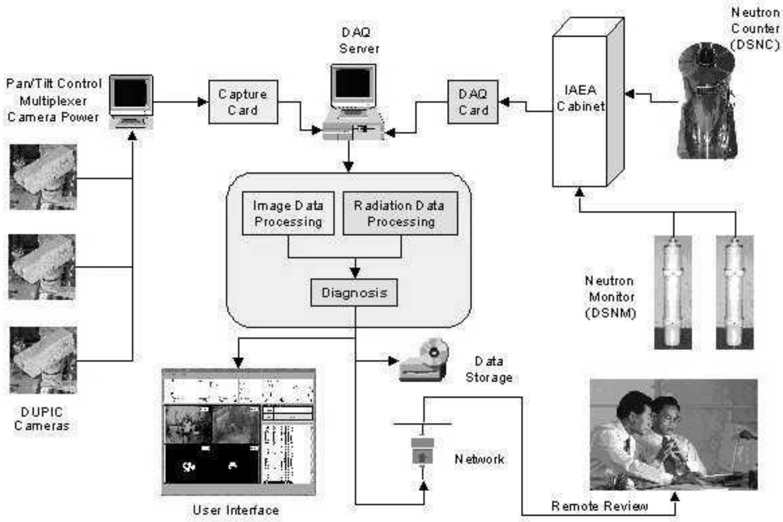

Figure 1. Schematic Diagram of DUPIC Intelligent Surveillance System.

integrated monitoring data as inputs, and generates detailed diagnostics of the spent fuel status event as outputs. The weight matrix of neural networks had been trained and verified in previously conducted cold test with actual data obtained from a series of spent fuel transport experiments.

2.1. Hardware Components

The overall structure of the C/S system consists of neutron detectors, color CCD (Charge-Coupled Device) cameras and a neural network based diagnostic system as shown in Figure 1. The cameras are connected to a multi-plexer to control and transfer the live images of the work area. The grabber board (Matrox Marvel G200 AGP) mounted on a PC is capable of performing fast image capture and high-speed image processing using a DSP (Digital Signal Processing) chips. As shown in Figure 2, there are one sealed door and two unsealed doors in the DFDF, and three CCD cameras are positioned at each door in order to monitor some activities related to the SF (spent nuclear fuel) movement to and from the doors.

Two DSNMs (DUPIC Safeguards Neutron Monitors) are located near the unsealed doors to detect any transportation of nuclear material through the doors. The cameras and DSNMs installed on the outside surface of the DFDF are cabled to the surveillance server located in the working area of the DFDF. Each neutron monitor (DSNM) installed at the DFDF includes two pairs of He-3 gas proportional counter tubes and a pre-amplifier to increase efficiency and reliability. They have no gamma shielding because they are located outside of the hot cell, and their structures are constructed with high-density polyethylene, which also has the function of neutron moderation. For the quantitative measurement of SNM contents, the DSNC (DUPIC Safeguards Neutron Counter) is located in the hot cell[4].

The signals from the DSNMs and DSNC are acquired with a DAQ (Data Acquisition) card that has four input channels and simply counts the number of neutrons detected. The personal computer takes the image signal and the radiation signal periodically, analyzes them, and diagnoses the transportation status to report the result to the remote client. The signals of DSNC and DSNMs are shared with the data cabinet of the IAEA.

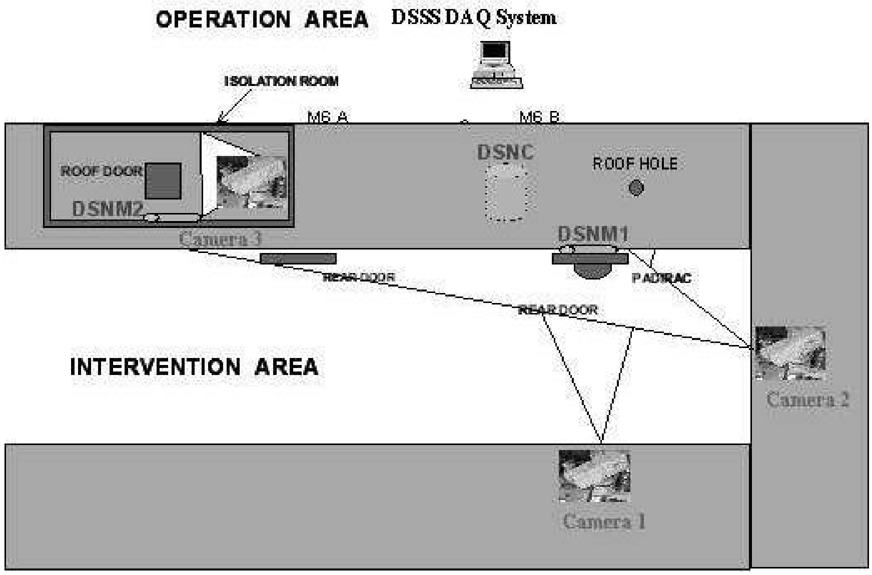

Figure 2. Installation Map of DISS at DUPIC Fuel Development Facility.

2.2. Software Components

2.2.1. Monitoring Software

The software of DUPIC Intelligent Surveillance System (DISS) has been developed based on the Microsoft Windows 98®. As the system is designed to process both the radiation signals and 1~2 frames of images in a second, it could be considered as a near real-time surveillance system concerning the speed of currently available image processing chip. The system functions could be summarized as follows. At every 5 seconds, image and radiation data are collected from the channels of image signal and neutron monitors. At each time, the spatial image data is converted into a temporal data through image processing and stored into a memory buffer. At the end of each time window, the temporal data sets stored over two time horizon – the current and a prior one – are processed to extract characteristic feature. If the diagnostic result reveals anomaly, the raw image data of the respective time interval are stored in recording device. Otherwise, the prior temporal data is removed from the buffer and data acquisition process is continued over an updated time horizon

The data periodically acquired are processed to feed to the diagnosis routine, where the level and variance of the radiation data, the position and size of the objects in the image data are evaluated by data processing module. The transportation diagnosis program has two stages of diagnostics mode, the individual mode and the overall mode. In the individual mode, the radiation transportation status based on radiation data and the object transportation status based on image data is analyzed separately, and in the overall mode the two results are unified to make an overall diagnosis about facility status. In the individual mode, the diagnosis routines of both radiation and image determine the transportation status to one of the five cases of 'No Detection', 'Near', 'Fade In', 'Rest', and 'Fade Out'. In the overall mode, a more sophisticated diagnosis will be performed based on the results of the individual mode and the raw data.

2.2.2. Radiation Data Review

The electronic signals from the radiation detectors are transferred to the portable shift register, where it is selectively counted as single and coincident neutron counts. These data are then collected at PC and analyzed through interface software. From the radiation data review module, therefore, the system may only determine the changes of SNM position as a five categories as mentioned before. As the dimension of the radiation data (number of neutrons) is simple and clear, an algorithm is used here to infer the behavior of SF. For the diagnosis of nuclear material' s behavior, the slope of the five successive numbers of detected neutrons is used. For example, if the run number is 50, then the diagnosis is performed based on the previous five data, run number from 46 to 50. Therefore, it is reasonable to say that the radiation diagnosis is performed based on the trend of radiation intensity in recent 30 seconds. When a SNM start to move from stationary position, therefore, the system can identify the abnormal status in 10~20 seconds after first data acquisition.

As the radiation particles are emitted from SNM in random manner and the intensity slope is calculated from five data only, statistical fluctuation should be considered in the module. When the material is in a stationary location, the fluctuation would cause the slope to be larger then zero and to lead faulty diagnosis. To avoid faulty diagnosis due to the fluctuation, we adopted some threshold values based on the Chi-squared goodness of fit test[5].

Generally, χ^2 tests are used for determination of goodness of fit between theoretical results and experimental results as follows;

$$c^2/d.o.f. = \frac{\sum_{i=1}^{T} \frac{(N_T - N_i)^2}{\Delta N_i^2}}{(T-1)} \qquad (2.1)$$

where, N_T is theoretical value,
N_i is experimental value,
d.o.f. is degree of freedom,
DN_i is error value of N_i.

When this value is near one, the theoretical results show a good agreement with experimental results, otherwise not. If the SNM located in a stationary position and N_i is the number of radiation detected, this value follows the Gaussian distribution. Considering the statistical fluctuation only, DN_i is equal to N_i. In the case of stationary situation, expected number of radiation (theoretical) may constant to the time, and N_T could be estimated as an average value of N_i. As we are calculating the slope of radiation intensity from five recent data, T is equal to five. In this study, three radiation related measures; N, dN/dt, χ^2 are used as input parameters of neural networks for the intelligent diagnosis of SNM status.

2.2.3. Video Data Review

Visual surveillance data is a collection of image data in time series. At each time interval the following image processing procedures are used for intelligent diagnosis.

(1) Capture base image: Base image of the surveillance area is captured firstly. The base image is then converted into a binary image consisting of black and white pixels. Threshold value for the binary conversion is suitably selected from the gray level intensity histogram data of the scene. It is assumed that the lighting condition is maintained constantly throughout the surveillance.

(2) Identify change in the scene: At each sampling instance, a new scene is captured and converted into a binary image. Subsequently, a bit wise AND operation is performed with the base image. Any difference in the scene, for instance a new material entered in the area, will be displayed as a collection of black pixels.

(3) Identify the transported material: Perform connectivity analysis on the black pixels and label them according to the size of connected components. The largest connected components is identified as the transport cask and subsequently verified through pattern matching.

(4) Identify the position and distance of the cask: The position of the center point of the cask image (X_{CM}, Y_{CM}) and the distance from door (reference position) are determined by processed image data.

Through the above image processing procedure, the visual data that is spatial in nature is converted into a temporal data. This sets a basis for coherent integration of camera data with the radiation data in addition to the apparent benefit of data size reduction.

Based on the experimental data taken in last two years, the 1st version of the automatic diagnosis module for material transportation had been developed that is to be integrated into the intelligent C/S system. Some neural networks architecture, such as recurrent network, is known to be applicable to time series data, but it is difficult to train[6]. The data collected over a time horizon presumably contain all the information for characterizing the validity of the radioactive material transport. Thus, most common and effective architecture, self-organized feature mapping, is adopted in this module[7].

Specifically, the neural networks module accepts certain features extracted from the surveillance data as input and yields the status of the radioactive material. The distance of the cask from the reference position is drawn out by the image processing from the collection of the cask center positions. And then the slope of the 5 sequential distances is fed to the neural net, which diagnose the cask behavior. The input vector of the neural networks is consists of three parameters; distance of current object, R_u, averaged distance of the object, $\overline{R_u}$, slope of variation of the distance, dR_u/dt for run number u.

Normalization of data is necessary to maintain dimensional consistency of the input data of various natures. Before being presented into the network, the input data are normalized in the range of 0.1 to 0.9. After the network training, all weights of the connections are determined and the automatic diagnosis can be derived easily from the image responses.

3. Results and Discussion

The concept of the intelligent C/S system using neural networks has been developed for DUPIC facility since 1996, and the cold test of the system had been conducted in 1999. As the hot operation of DUPIC facility was started in 2000, a few activities related to SNM transportation was conducted and relevant field test of the C/S system had been conducted in last two years. Since the overall mode diagnosis is under development, only typical results of individual mode diagnosis are presented here. In the field test experiments, in general, spent fuel rod-cuts were transported into the hot cell as a following steps; (1) A cask containing one spent fuel rod-cut is approaching to the hot cell door, (2) the cask with one rod-cut in it is at rest, (3) the one rod-cut in the cask is being brought into the hot cell, (4) the empty cask is at rest, (5) five rod-cuts are being brought into the cask from the hot cell, (6) the cask with five rod-cuts in it is going away.

As shown in Figure 3, the radiation diagnosis results well describe the transportation status. The dots in the graphs show the radiation level and the hard line means radiation

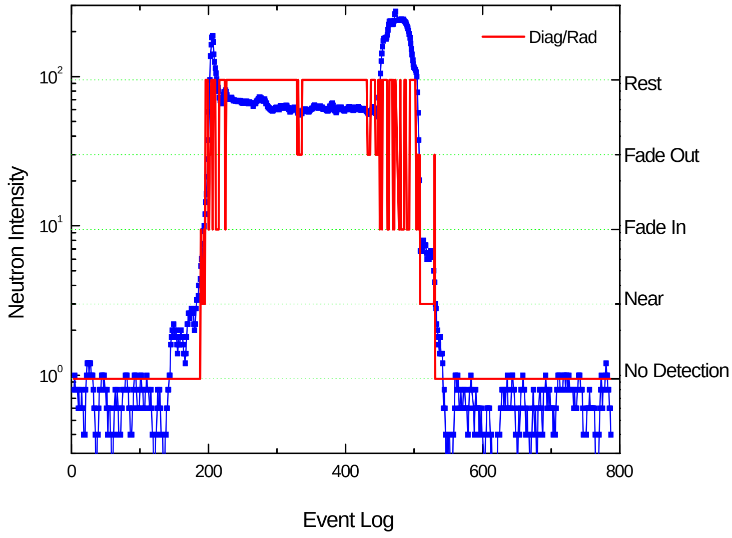

Figure 3. Intelligent Diagnosis of Cask Movements by SOM.

diagnosis. It was found that, the video image processing methodologies adopted in previous version of DISS occasionally resulted in incorrect identification of objects when the environment was cluttered or in the existence of specula backlighting as shown in Figure 4. And, the BP (Back Propagation) neural networks is limited to providing diagnostics within the trained domain only, whereas it is difficult to train the network for all possible safeguards events. Furthermore, the previous network architecture lacks incremental competency with system complexity. In other words, if a new sensor is added, the system has to be retrained entirely.

To overcome the limitations of previous system, therefore, a series of revision plan has been established through cooperative research in the following ways:

1) Enhance the integration of radiation and video data:

To overcome limitations in object recognition of the previous approaches, image-processing techniques should be improved to provide robust performance in the presence of a cluttered scene and/or specula backlighting. This could be accomplished by implementing color image processing and integrating data from multiple cameras. Unlike the gray level image, the composite of Red, Green and Blue spectrum of a color image can be separately processed to provide added reliability in object recognition. Further more, the use of multiple cameras enables redundant tracking of objects, and thus can effectively contribute to eliminating false identification.

2) Implementation of self-organizing neural networks:

To overcome the limitations of BP networks, another advanced neural network was needed to be adopted with the following characteristic requirements. It should have capability to be trained both in supervised and unsupervised mode. The capability to reorganize its structure is also needed so that new output categories can be generated rather than blindly trying to interpolate the outputs within the trained patterns when unrelated data are presented. Several types of unsupervised neural networks were considered for the revision of C/S system

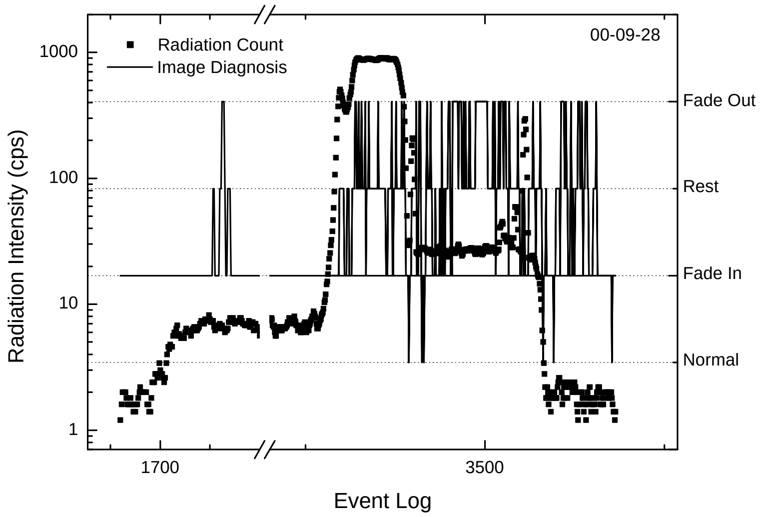

Figure 4. Diagnosis Results of Cask Movements by Previous Approach.

and preliminary test using SOM (self-organizing maps) model was conducted for reasonable data clustering of activities in DUPIC facility[9]. A key difference between the SOM and many other networks is that the SOM learns without supervision, hence the term self-organizing. The SOM typically has two layers: a self-organizing layer and an input layer that is fully connected to it. During training, a Euclidean distance is computed between the input vector and a weight vector associated with each neuron in the Kohonen layer. The neuron with the weight vector closest to the input vector is the winner. Neighboring neurons then adjust their weights to be closer to this same input-data vector. This adjustment is the learning mechanism. Thus, input vectors are grouped into areas represented by areas of the Kohonen layer.

As shown in Figure 5, it could be shown that the results of intelligent diagnosis well describe the transportation status except for the several unexpected situation. These kinds of mistake could be inferred from the integrity of training data and the performance of the system could be enhanced by the accumulation of experimental data

4. Conclusion

In this study, comprehensive surveillance strategies have been developed by combining advanced intelligent computational methodologies with advanced sensor technologies. Specifically, automatic integration and meta-analysis of video and sensor data combined with intelligent analysis is proposed to produce high-level diagnostics regarding abnormal operating patterns or sequences of events. By applying intelligent computational techniques, data from an array of diverse sensors and NDA (Non-Destructive Assay) devices can be integrated and analyzed to assist human operators and inspectors in determining safeguards and security problems ranging from sensor failures to material instabilities to material tampering or diversion.

A lab scale DUPIC facility safeguards system was successfully established with active support from the IAEA and US under the international cooperation program. With the

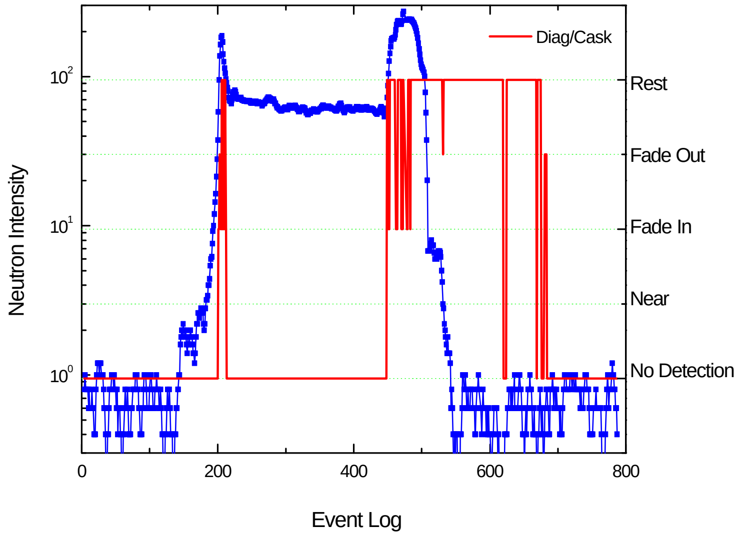

Figure 5. Intelligent Diagnosis of Radiation Monitoring by SOM.

experience gained from the lab scale facility and further advancement of safeguards technology development, a model safeguards system for the pilot scale facility is foreseen in the future. The R&D efforts for DUPIC C/S system will continue to stabilize and enhance the performance of the system through the integration of gamma monitoring system and remote monitoring using VPN. It is expected that remote monitoring will become a vital tool in enhanced cooperation of streamline inspection efforts of the IAEA and the Korea. It also expected that the remote monitoring system under construction in DFDF could contribute to promote the non-proliferation transparency of DUPIC study.

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