**Radiation Exposure and Cancer Risk: Intelligent Modeling**

**ABSTRACT**

From an experimental point of view, each organ is subject to cancer from a certain dose threshold. This is easily verifiable in the laboratory. However, there are uncertainties. Uncertainties related to human physiology itself. The same organ reacts differently from one person to another. Other uncertainties are related to the radiation doses received. The studies carried out on these subjects which relate cancers by irradiation are distinguished by their vagueness. This varies according to exposure history, exposure time and calculation assumptions. The classical mathematical analysis tools quickly reach their limits in this kind of data analysis. In this study, we found it useful to propose an intelligent system based on the principles of fuzzy inference. The proposed system takes into consideration input variables such as (gender, age, and target organ). The rate of risk of attainment of each organ expresses the output variable. A rule base is established. The result is an application from which it will suffice to randomly introduce values to the input variables to instantly read the result at the output. This calculated result takes into account all uncertainties and inaccuracies related to the nature of the input variables. A dose of 0.1 Gy is fixed in advance for all tests.

Keywords: radiation exposure, cancer, fuzzy logic, modeling

**INTRODUCTION**

Triggering an alert to the effects of radiation is only reported when the threshold reaches a level outside the norm. This will enable rapid response and is also as evaluation of these effects used [1]. The exposure history is important in the analysis to understand the effect. However, multiple exposures in terms of exposure time and dose produce different effects. This dose produces an effect on the whole body or on each organ separately. Also, each member has his own sensibility. Depending on the type of exposure, duration, dose and according to the body concerned, a type of cancer can develop.

Risk projection methods allow for timely assessment of the potential magnitude of radiation related cancer risks following low-dose radiation exposures. The low-dose radiation exposure specify site cancers: stomach, colon, liver, lung, breast, uterus, ovary, prostate, bladder, thyroid, leukemia, oral, esophagus, gallbladder, pancreas, rectum, kidney and brain/central nervous system [2]. The risk of ionizing radiation covers solid cancers such as cancers of the lung, prostate and breast.

Analyses show that even at low doses, there is a link between the dose of radiation and all types of cancers other than leukemia. Also, the effect of radiation appear in other types of cancers such as lung cancer even after excluding the effects of carcinogenic factors such as smoking or atmospheric pollutants in the workplace. The effect of socioeconomic status is also likely to be a poor indicator of factors relate to social class differences in mortality, and suggests the possibility of residual confounding cancer radiation associations by socio-economic status. Excluding workers who carry the risk of contamination by other pollutants, the estimated association between radiation dose and mortality from colon cancer was higher than the estimate for the entire cohort [3]. All this suggests the evidence of the effect of radiation on the appearance of solid cancers and that, even at low doses. It is necessary to examine solid cancers related exhibitions. The results are often estimates given the uncertainty [4].
METHOD

Types of cancer data studied are from Data collected by RadRAT: A Radiation Risk Assessment Tool for Lifetime Cancer Risk Projection. Analyzes data represents the risk of cancer associated with exposure to radiation. The study sample included 1000 persons. These values are taken according to age at the time of exposure in correspondence with the registered cancer. The development of these cancers is due to chronic exposure to 0.1 Gy.

The prevalence proportions were calculated for persons, and the total prevalence counts are based on 2006-2011 by age, sex and races [2].

Fuzzy logic inference
Fuzzy logic is a sub-field of intelligent systems, it is widely used to solve a variety of problems in medical and biological applications. One of the most important fields of application of fuzzy set theory developed by Zadeh in 1965 [5] is based on rules. These systems are an extension of conventional rule-based systems. In a broad sense, a fuzzy rule-based system is a system based on rules where fuzzy logic is used as a tool to represent different forms of knowledge about a problem and to model the interactions and relationships between its variables. Due to this property, the principles of fuzzy logic have been successfully applied to a wide range of problems in different areas where the uncertainty and vagueness emerge in different ways. Fuzzy modeling [6], the fuzzy control [7] and fuzzy classification are the most common applications.

Fuzzy logic deals with reasoning on a higher level, using linguistic information acquired from domain experts. The above-mentioned capabilities make fuzzy logic a very powerful tool to solve many medical problems, where data may be complex or in an insufficient amount. The fuzzy logic concept provides a natural way of dealing with problems where the source of imprecision is an absence of sharply defined criteria rather than the presence of random variables [8]. The fuzzy approach considers cases where linguistic uncertainties play some role in the control mechanism of the phenomena concerned [9]. Fuzzy inference systems (FIS) are powerful tools for the simulation of nonlinear behaviors with the help of fuzzy logic and linguistic fuzzy rules [10].

For example, there is not a straight-line relationship between the sex, age and organ cancer incidence. In this study, we take to decision algorithms using the engine that makes inferences on a fuzzy rule system. For all the algorithm presented below there is a common rule form for rules that associate an observation vector.

\[ a = (a(1), a(2), \ldots, a(n)) \]

with a diagnosis.

Further, we assume the following general form of the kth rule in the system ( \( k = 1, 2, \ldots, K \)):

If \( a(1) \) is \( A_{1k} \) AND \( \ldots \) AND \( a(n) \) is \( A_{nk} \) THAN \( b \) is \( B_k \)

where \( A_{ik} \), are fuzzy sets (whose membership functions are designated by \( m_{Ai,k} \)) that correspond to the nature of particular observations (for simplicity we assume the sets to be triangular fuzzy numbers) whereas \( k \cdot B \) is a discrete fuzzy set defined on the result set, with the \( B_k \) membership function.

The particular decision algorithms to be used in organ effect have in common both the inference engine and the procedure for rule system derivation from the learning set. In the protoformal deduction rule, the syllogism:

\[ Q_1 \text{A’s are } B’s \text{ AND } Q_2(A&B)’s \text{ are C’s THAN } Q_1Q2A’s \text{ are } (B&C)’s \]

Fuzzy Logic Modeling
A most studies interest exists for evaluating the relationship between the different factors and lung cancer. In our case, we can introduce the relationship between age, sex, years and race as inputs variables and the prevalence of cancer as output variable (Figure 1).

Fuzzification of variables
This step consists to convert numerical values to linguistic expressions. The inputs and output are classified into three linguistic categories:

The variable ‘Age’ is fuzzified on [installment 1 “0-7 years”, installment 2 “8-11 years”, installment 3 “9-17 years”, installment 4 “16-21 years”, installment 5 “19-26 years” and installment 6 “over 24 years”] (Figure 2).

The variable ‘Race’ is fuzzified on [Whites, Blacks, Hispanics, and Asian/pacific islanders] (Figure 3).

Fuzzy logic modeling
A most studies interest exists for evaluating the relationship between the different radiation exposure and cancers. In our case, we can introduce the relationship between age at exposure, sex, cancer following a chronic exposure to 0.1 Gy and races as inputs variables and the organ patient cancer as output variable (Figure 1).
Fig. 1 Bloc system of model

**Fuzzyfication of variables**

This step consists to convert numerical values to linguistic expressions. The inputs and output are classified into three linguistic categories:

The variable ‘Age’ is fuzzyfied on [Young, Adult and Old] (Figure 2).

The variable ‘Sex’ is not fuzzyfied, we attribute ‘1’ for female and ‘2’ for male (Figure 3).

The variable ‘organ patient cancer’ is not fuzzyfied, we attribute a number for each organ cancer (Figure 4).

As it is impossible to define clear boundary between these categories, we considered them as fuzzy variables and therefore we created fuzzy intervals between the different membership functions to overcome these uncertainties.

Fig. 2 Fuzzyfication of ”Age”

Fig. 3 Representation of ”Sex”
CONCLUSION

(i) The artificial intelligent system using fuzzy logic method could extend our understanding of radiations effects. The intelligent software created in this study could be used for prevention of impact and its degree of cancer nature. The goal of this study is to design and perform a pilot investigation which will provide preliminary data. The result of the fuzzy program so far, is a numeric and symbolic terms of age and sex and impact of electromagnetic radiations, using the fuzzy inputs linguistic data in the universe of discourse (Young, Adult and Old).

As the input parameters are characterized by uncertainty, we believe that this tool is very adequate. We emphasize that our fuzzy system is not meant to replace or substitute for an experienced analyst; on the contrary, we envisage that the fuzzy logic system should be viewed as a decision support in the most accurate. Once the system is established, it allows to predict the impact of each input and its effect on the output parameter. Assessing the degree of impact allows us to predict the type of cancer resulting. The result recorded in output system is the contribution of the set of input variables, taking into account inaccuracies and the complexity involved in the process.

Since it is impossible to anticipate and quantify future developments that might cause a change in the number of people diagnosed with cancer, these projections should be interpreted as only indicative of future trends. Figure 5 shows an example application when the sex is female (1) and the age is 29.8 years old, the organ will be concerned by cancer is (3) corresponding to breast cancer.
References


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