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*Research Article*

# Classifying Cervical Spondylosis Based on Fuzzy Calculation

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Conventional evaluation of X-ray radiographs aiming at diagnosing cervical spondylosis (CS) often depends on the clinic experiences, visual reading of radiography, and analysis of certain regions of interest (ROIs) about clinician himself or herself. These steps are not only time consuming and subjective, but also prone to error for inexperienced clinicians due to low resolution of X-ray. This paper proposed an approach based on fuzzy calculation to classify CS. From the X-ray of CS manifestations, we extracted 10 effective ROIs to establish X-ray symptom-disease table of CS. Fuzzy calculation model based on the table can be carried out to classify CS and improve the diagnosis accuracy. The proposed model yields approximately 80.33% accuracy in classifying CS.

## 1. Introduction

Due to the development of the society and the change of environment, patients with signs and/or symptoms of cervical spondylosis (CS) are frequently encountered in spinal practice and, for the time being, the incidence of the CS is more than before. But the exact numbers of prevalence or incidence are unknown [1]. From the social and economic point of perspective, it is really imperative to diagnose the CS as early as possible. Therefore, in recent years, the research on CS has been a hot topic [2–7].

Currently, the clinical diagnostic methods [8–10] of CS technology include the clinical examination, spinal angiography, vertebral artery angiography, X-ray, computed tomography (CT), and magnetic resonance imaging (MRI). For the time being, X-ray inspection results in the basic-level hospitals of China about the diagnosis of CS are still given priority because X-ray is the most cost-effective imaging modality for the diagnosis of CS due to its low costs, radiation dose, and flexibility of being able to image spine in different poses (standing, flexion, extension, bending, or torsion), while MRI (e.g., T2-weighted imaging) evaluating pathological changes in the disease is of limited use due to the weak correlation between the MR findings and clinical symptoms [11–13]. So the X-ray radiographs of CS are still very important and necessary.

Yet, the accuracy of the disease diagnosis depends on clinical doctors' medical knowledge and clinical experiences of the individual, which can result in the process of clinical diagnosis for the same disease diagnosis between different doctors who can produce some deviation. So one more reasonable way is to obtain the images; if we could have an expert system to fully mix a lot of very experienced doctors' knowledge, we can make a classifying CS diagnosis system, which will allow our medical to greatly increase the diagnosis level, to simplify the doctor's work burden, and also to improve the efficiency of patients' medical treatment.

However, different types of CS in the mild stages of the disease and age-related changes, which are frequently seen in healthy aged people, have to be discriminated from the minimal disease-specific changes. These minimal changes in the X-ray images make visual diagnosis a difficult task that requires experienced experts. Even with this problem still unsolved, the potential of computer-aided diagnosis (CAD) has not been explored in this area as we know. Now we use the fuzzy calculation method [14, 15] to construct a fuzzy model of classifying CS.

Based on the above discussion, this paper puts forward the method of fuzzy calculation, which can be used to solve the problem of CS in the aspect of clinical classification. The fuzzy calculation is based on a number of orthopedic experts of CS clinical classification diagnosis level [15, 16] and it can avoid a single doctor in the diagnosis of the subjective factors and make the results more objective.

We altogether collected 1024 cases which were diagnosed clearly by X-ray, CT, and MRI in combination with clinical diagnosis of CS and combined with the literature data statistical analysis. Fuzzy calculation can be used to determine the number of uncertain phenomena. On the basis of the statistical data, the fuzzy logical way of thinking can establish the fuzzy relationship matrix; then using the fuzzy calculation approach we can get precise conclusion that for the application of fuzzy calculation in the field of medicine, has laid a solid theoretical basis. This paper adopts the fuzzy calculation in the maximum membership degree principle to establish mathematical model in order to implement quantitative diagnosis after using the computer, which can make the doctors in the clinical diagnosis of CS achieve quantitative diagnosis and lay a solid foundation and improve the accuracy in clinical diagnosis of CS, for clinical diagnosis of CS with classification provides certain guiding value.

The paper is organized as follows. Sections 2 and 3 provide a background on CS and fuzzy logic calculation. Section 4 summarizes the main ROIs where the CS becomes observable during its early stage and shows the image acquisition setup as well as lots of template-based experiences from experts of orthopedics department which can be used to obtain a precise and anatomically standardized model of the functional vertebrae cervical. Section 5 shows the experiments that were proposed and carried out in order to evaluate the proposed fuzzy calculation as a diagnostic tool for the classification of the CS.

## 2. Background of CS

CS is defined as age-related chronic disc degeneration. It is also referred to as vertebral osteophytosis secondary to degenerative disc disease, which in the cervical spine may be asymptomatic or can present as pure axial neck pain, cervical radiculopathy, cervical myelopathy, or cervical myeloradiculopathy [2, 17, 18]. The progression of spondylosis changes may lead to spinal stenosis or narrowing of the spinal canal. Spinal cord or nerve root function may be influenced, giving rise to symptoms of myelopathy or radiculopathy [19].

In the Chinese diagnosis, clinical classification of the CS mainly includes four types: (i) CS radiculopathy (CSR), (ii) cervical spondylotic myelopathy (CSM), (iii) vertebral artery type of CS (VACS), and (iv) sympathetic CS (SCS).

All sorts of different types of CS are given priority with local symptoms in the early stage, for example, neck and shoulder pain, anaemia, dizziness or numbness in upper limbs and fingers, unsteady walking, or unsteady gait. Local pain of the neck is a common symptom; transient upper limbs and fingers numb, weak hand, and fine motor with a sexual dysfunction are a common performance.

In the traditional diagnosis, we often use the symptoms we mentioned above to make the final decision. Its diagnosis is based on the information provided by a careful clinical examination, a thorough interview of the patient and relatives, X-ray, CT, and so forth. However, X-ray is frequently used as a complimentary diagnostic instrument in addition to the clinical discovery in the basic-level hospitals. Due to the fact that CS has different classification, different types of CS need to be treated with different treatments and different types of CS have to be discriminated from the minimal disease specific changes in the X-ray images. These minimal changes in the X-ray images make visual diagnosis a difficult task that requires experienced explorers. Even with this, problem was still unsolved and the potential of automated diagnosis algorithm has not been explored in this area. So the fuzzy calculation method of classifying CS has certain practical significance.

## 3. Fuzzy Logic Calculation

In recent years, many complex problems have been solved developing computational intelligence systems. Fuzzy logic has been proved to be a powerful tool as decision-making systems, such as pattern classification systems and expert diagnostic platform [20]. Fuzzy logic theory has been used in some medical expert systems for instance [21–25].

*3.1. The Definition and Mathematical Representation of Fuzzy Subsets.* Giving conclusive domain $U$, $U$ to closed interval $[0, 1]$ any mapping $u_{\underline{A}}$

$$\begin{aligned} u_{\underline{A}} &: U \longrightarrow [0, 1], \\ u &\longrightarrow u_{\underline{A}}(u). \end{aligned} \tag{1}$$

Define $U$ to get a fuzzy subset $\underline{A}$. $u_{\underline{A}}$ is called the membership of fuzzy subsets. $u_{\underline{A}}(u)$ is called as a membership of $u$ for the fuzzy subset $\underline{A}$. The scope of $u_A(u)$ is $[0, 1]$. The size of the $u_{\underline{A}}(u)$ reflects $u$ for subordinate degree of fuzzy subsets. $u_{\underline{A}}(u)$ values closing to 1 indicate a fuzzy subset $u$ belonging to $A$ for a very high degree. $u_{\underline{A}}(u)$ values closing to 0 indicate a fuzzy subset $u$ belonging to $A$ for a very low degree. Therefore, the fuzzy subset consists entirely of membership function to be described.

*3.2. Method of Determining the Membership Degree Function.* Membership function, in which the process of determining in nature is objective, is the quantitative description of fuzzy concept. Because the understanding that everyone on the same fuzzy concept exists deviation, the determination of membership function also has been subjective. Usually, we can construct membership function by the following ways: (1) fuzzy statistical method: we can use the method of fuzzy statistical experiment to determine the membership degree function, but it is with heavy workloads, (2) example method: from the known finite $u_{\underline{A}}$ values to estimate the membership function of fuzzy subsets $\underline{A}$ in domain of $U$, and (3) expert experienced method: according to the practical experience of experts to determine the membership function.

*3.3. The Foundation of a Fuzzy Calculation Model.* From the fuzzy logic calculation we know that it can be provided with generalized disease symptoms (including symptoms, signs, X-ray characterization, etc.), space $Q, q \in Q, q$ is a generalized symptom. The first $j$ disease that named $A_j$ is a subset of the symptoms of disease on $A$ and each generalized symptom of disease $q$ can determine a mapping from the $A_j$ or relative frequency.

If the number of cases that $S_{ij}$ appears as symptoms $q_i$ of disease $A_j$, $q_i$ is the total cases of disease $A_j$, then define

$$U_{Aj}(q_i) = \alpha \frac{S_{ij}}{d_i} \quad \left(\frac{S_{ij}}{d_i} \geq 0.1\right) \tag{2}$$

or

$$U_{Aj}(q_i) = -\alpha\left(1 - \alpha\frac{S_{ij}}{d_i}\right) \quad \left(\frac{S_{ij}}{d_i} < 0.1\right). \tag{3}$$

Among them, $S_{ij}/d_i$ is the relative frequency of $d_i$ symptoms appearing in the $A_j$. $\alpha$ is the weight coefficient, and let $\alpha = 1$; then $U_{Aj} \in [-1, 1]$; let $\alpha = 10$, $U_{Aj} \in [-10, 10]$.

Mapping of the two types (2) and (3) is not visible and normal in *Zadeh* $[-1, 1]$ space but it is multivalued maps, which can be called the mapping of the generalized *Zadeh* spaces, instead of two-valued mapping.

If we use (2) only to define the membership function, let $\alpha = 1$, and remove the constraint condition of $S_{ij}/d_i \geq 0.1$, then the membership function is in the mapping of normal *Zadeh* space $[0, 1]$.

By (2) and (3) we can obtain symptoms of disease relationship matrix $R$; here we can use the way of assumption and other rights, which let the power component be 1. Adopt the $*(\cdot, +)$ operator of synthetic fuzzy matrix, according to the maximum membership principle to make different diagnosis of diseases as follows:

$$b_i = \sum 1 \cdot r_{ij}, \tag{4}$$

$$m = \max b_j. \tag{5}$$

The final formula (5) said in disease diagnosis, according to the principle of maximum membership for syndrome diagnosis.

Let $U_{Aj}(q_i) = S_{ij}/d_i = r_{ij}$; this is the normal *Zadeh* space $[0, 1]$ mapping. For each patient, we can get from Table 1 a fuzzy matrix of 10 rows and 4 columns about X-ray disease symptoms of CS, named $R_{10\times4}$. We can synthesize the fuzzy matrix according to (4); then (5) can be used to diagnose disease according to the maximum membership degree principle.

## 4. ROIs of CS X-Ray Radiographs Acquisition and Processing

*4.1. Image Acquisition.* Radiographs for diagnostic medical imaging have been used for many years. The diagnostic results are based on the visual pattern recognition by trained radiologists and doctors. In this paper, we tried to mimic the radiologists' diagnostic viewing steps.

General information: in 1024 patients, 588 male cases and 436 female cases, 21 to 91 years old, average 53.5 years old. All through history and cervical spine X-ray confirmed CS incidence to some extent, the patients had different degrees of shoulder, neck, and occipital pain; neck shoulder pain radiates into the arms fingers numbness, decrease in muscle strength, different degree feeling obstacle, shoulder and upper extremity lateral cold, dizziness, neck activity with headache, dizzy numb to aggravate body movement, and so on.

Method equipment: Toshiba DGW-20A 500 mA X-ray machine and Toshiba WINMIND DFX-1000A 800Ma X-ray machine. Material: average 10 × 12 inches X-ray films. This inspection should be under fluoroscopy. Patients stand before the bed in the examination, taking neutral position, under the perspective of localization. Regularly there were X-ray films and left/right inclined 45 degrees of inclined position. If necessary, intake mouth and flexion-extension (FE) radiographs. Film distance is 110 cm. Together with lumbar spondylosis, cervical degenerative disease is one of the most common problems seen by medical care personnel [12]. It is important to observe hook vertebral joints, intervertebral disc, intervertebral foramen, and intervertebral facet joints.

*4.2. Extract ROIs and Processing.* From the X-ray of CS manifestations, we can extract 10 effective regions of interest (ROIs) in order to establish X-ray symptom—disease table of CS. The 10 ROIs are as follows: (i) vertebral dislocation, slippage, (ii) physiological curvature became small, stiff, partly recurvatum, and posticous; (iii) narrowness of intervertebral disc space, and the predilection site is C4-5, C5-6, C6-7 and others in turn; (iv) the intervertebral foramen becomes small and deformed; the predilection site is C5-6, C6-7-5, and C4 in turn; (v) osteoproliferation: the edge of vertebra with bony hyperplasia, bone sclerosis, osteophytes, or bony bridge; the uncovertebral joint, facet joint bone hyperplasia; lumbar intervertebral disc adjacent edge grinding angle change and the free body of front edge; (vi) the anterior longitudinal ligament calcification; (vii) ossification of posterior longitudinal ligament; (viii) nuchal ligament calcification; (ix) abnormal position change with ring gear joint and atlantoaxial joint; (x) small joint, double arc shadow or bilateral shadow behind vertebral body. Select the 10 generalized symptoms of CS X-ray as characteristic symptom set and use more samples to sample a certain frequency of some symptoms in the disease; matrix is established between the generalized symptoms versus diseases (as shown in Table 1).

## 5. Evaluation Results

This section shows our experimental results carried out in order to evaluate the performance of the classification system and its utility as an auxiliary tool for classifying CS. First, a fuzzy recognition model based on the fuzzy calculation paradigm is implemented for reference. Second, the experimental results that were conducted to evaluate the proposed fuzzy calculation model are shown.

Table 1: CS Symptoms versus Types.

| No. | General symptoms | CSR 0.6593 | CSM 0.1405 | VACS 0.0962 | SCS 0.1040 |
|---|---|---|---|---|---|
| | X-ray manifestation | | | | |
| 1 | Vertebral dislocation, slippage | 0.0356 | 0.0347 | 0.0408 | 0.0374 |
| 2 | Physiological curvature became small, stiff, partly recurvatum, and posticous | 0.4548 | 0.4514 | 0.4490 | 0.4579 |
| 3 | Intervertebral disc narrow | | | | |
| | C4-5 | 0.4607 | 0.4583 | 0.4694 | 0.4579 |
| | C5-6 | 0.3185 | 0.3194 | 0.3163 | 0.3178 |
| | C6-7 | 0.3067 | 0.3056 | 0.3061 | 0.3084 |
| | Others | 0.0756 | 0.0764 | 0.0816 | 0.0748 |
| 4 | Intervertebral foramen deformation, diminish | 0.7111 | 0.7083 | 0.7143 | 0.7103 |
| 5 | Osteoproliferation | 0.9985 | 1 | 1 | 1 |
| 6 | Ossification of anterior longitudinal ligament | 0.1052 | 0.1111 | 0.1010 | 0.1038 |
| 7 | Ossification of posterior longitudinal ligament | 0.0904 | 0.0903 | 0.0909 | 0.0849 |
| 8 | Ossification of ligamentum nuchae | 0.7748 | 0.7778 | 0.7677 | 0.7830 |
| 9 | Abnormal position change with ring gear joint and atlantoaxial joint | 0.0444 | 0.0417 | 0.0404 | 0.0472 |
| 10 | Small joint double arc shadow or bilateral shadow behind vertebral body | 0.1126 | 0.1111 | 0.1111 | 0.1132 |

1024 cases in all.

### 5.1. Clinical Application

*Example 1.* Male, 46-year-old, worker, June 18, 2013. Neck stiffness, shoulder strength feeling, mental fatigue, and dizziness recently for 1 year. Recently, dizziness aggravated. Half month before, he fainted on the ground when he went to toilet at midnight. The faint lasted for 25 minutes before awaking. X-ray showed C3-7 posterior marginal osteoproliferation and different state of intervertebral disc space and C5 rear nozzle sample protrusions; physiological curvature becomes straight. From the CT examination, we can know that head and brain are nothing abnormal. According to the above complaints and X-ray and CT examination, the final clinical diagnosis is vertebral artery type of CS. Afterwards, we can diagnose the disease through the fuzzy model established above. The steps are as follows.

According to the complaints and the X-ray manifestations of the patient, we can separate out the relationship between the generalized X-ray symptoms of the patient and diseases from Table 1. As shown in Table 2.

In Table 2, membership of generalized symptoms of X-ray, which failed to collect, uses 0 to fill. According to (4) and (5), we can get the calculation results as follows:

$$\underline{B} = (2.6184, 2.6111, 2.6224, 2.6168). \tag{6}$$

Use the formula

$$X_i' = \frac{X_i}{\max X_i}. \tag{7}$$

Normalized to

$$\underline{B}' = (0.9971, 0.9957, 1, 0.9979), \qquad M = \frac{1.0}{\text{VACS}}. \tag{8}$$

The final clinical diagnosis of CS is vertebral artery type which is consistent with the result of classifying based on fuzzy calculation model we established.

*5.2. Testing Results.* In medical statistics, we usually express diagnostic test performance by the terms: accuracy, sensitivity, and specificity. When a single test is performed, the person may have the disease (positive) or may not (negative). As we all know, an ideal test should have high accuracy, high sensitivity, and high specificity. We define these accuracy measures as follows.

(A) *Accuracy*. We measure the accuracy as the ratio of the number of correctly classified CS ($N_r$) to the total number of CS ($N$). Consider

$$\text{Accuracy} = \left(\frac{N_r}{N}\right) \times 100\%. \tag{9}$$

(B) *Sensitivity*. It is defined as the probability that the test claims a person has the disease (positive) when in fact he has it (true positive). And it is defined by

$$\text{Sensitivity} = \left(\frac{\text{TP}}{(\text{TP} + \text{FN})}\right) \times 100\%. \tag{10}$$

(C) *Specificity*. It is defined as the probability that the test says a person does not have the disease (negative) when in fact he does not (true negative). And it is defined by

$$\text{Specificity} = \left(\frac{\text{TN}}{(\text{TN} + \text{FP})}\right) \times 100\%. \tag{11}$$

In this experiment diagnosis task, FP is the number of false positives (actually it is not this type of CS, but testing

Table 2: CS Symptoms versus Types.

| No. | General symptoms | CSR | CSM | VACS | SCS |
|---|---|---|---|---|---|
| | X-ray manifestations | | | | |
| 1 | Vertebral dislocation, slippage | 0 | 0 | 0 | 0 |
| 2 | Physiological curvature straighten, ending bow | 0.4548 | 0.4514 | 0.4490 | 0.4579 |
| 3 | Intervertebral disc narrow | | | | |
| | C4-5 | 0.4607 | 0.4583 | 0.4694 | 0.4579 |
| | C5-6 | 0.3185 | 0.3194 | 0.3163 | 0.3178 |
| | C6-7 | 0.3067 | 0.3056 | 0.3061 | 0.3084 |
| | Others | 0.0756 | 0.0764 | 0.0816 | 0.0748 |
| 4 | Intervertebral foramen deformation, diminish | 0 | 0 | 0 | 0 |
| 5 | Osteoproliferation | 0.9985 | 1 | 1 | 1 |
| 6 | Ossification of anterior longitudinal ligament | 0 | 0 | 0 | 0 |
| 7 | Ossification of posterior longitudinal ligament | 0 | 0 | 0 | 0 |
| 8 | Ossification of ligamentum nuchae | 0 | 0 | 0 | 0 |
| 9 | Ring pivot joints abnormal changes of position | 0 | 0 | 0 | 0 |
| 10 | Small joints, double arc, or trailing edge bilateral vertebral bodies | 0 | 0 | 0 | 0 |

result belongs to this type), TP is the number of true positives (correctly diagnosed types of CS), FN is the number of false negatives (misclassified CS), and TN is the number of true negatives (actually it is not this type of CS, and testing result does not belong to this type). Below, we show the evaluation on our dataset, Tables 3, 4, 5, 6, and 7.

We randomly selected 300 cases from database to evaluate and got the results: Table 3 to Table 6, respectively. We can also, respectively, obtain the accuracy, sensitivity, and specificity calculated by (9), (10), and (11) as shown in Table 7.

Table 3: Evaluation about CSR.

| | Gold standard | |
|---|---|---|
| | CSR | Non-CSR |
| Testing results | | |
| CSR | 143 (TP) | 27 (FP) |
| Non-CSR | 48 (FN) | 82 (TN) |

Table 4: Evaluation about CSM.

| | Gold standard | |
|---|---|---|
| | CSM | Non-CSM |
| Testing results | | |
| CSM | 35 (TP) | 52 (FP) |
| Non-CSM | 10 (FN) | 203 (TN) |

Table 5: Evaluation about VACS.

| | Gold standard | |
|---|---|---|
| | VACS | Non-VACS |
| Testing results | | |
| VACS | 28 (TP) | 14 (FP) |
| Non-VACS | 4 (FN) | 254 (TN) |

## 6. Discussion

For modern general population, ageing of population and power of work contribute to a rise in the consumption of health care in the aspect of CS. CS has become the common frequently occurring disease in our daily life and causes serious damage to human health and impedes the normal life of people, and the incidence of CS shows a trend of obvious rise among young people in recent years.

There are lots of literatures working on the detection of vertebrae diseases, most of which work on X-rays because of many reasons including the availability of clinical data. In addition, most existing literatures detect vertebrae with segmentation for automating the diagnosis of osteoporosis which can be diagnosed from X-ray or dual X-ray images for estimating bone mass and as clinical standard.

Smyth et al. [26] and Roberts et al. [27] presented approaches with an active shape model (ASM) to quantify the bone mass for osteoporosis diagnosis and help in early diagnosis of osteoporosis and its clinical trials treatments, respectively. Mastmeyer et al. [28] exploited a new hierarchical 3D technique, which segmented the vertebral bodies in order to measure bone mineral density (BMD), with high precision in volumetric CT datasets. Tan et al. [29] used high-resolution CT images to develop an algorithm that provides quantitative measures of the syndesmophytes where these abnormal bone structures grow at intervertebral disc spaces. Cherukuri et al. [30] presented a technique of image processing making full use of convex hull-based features of X-ray to research the bony growth on vertebrae: osteophytes. Kasai et al. [31] presented a computerized approach to detect the vertebral fractures on lateral chest X-ray radiographs which could assist radiologists to interpret image.

It is worth to point out that there is an algorithm to classify CS. So our research tried to use the fuzzy calculation method for the first time to make classification diagnosis of CS. This paper shows a preliminary fuzzy algorithm for classifying CS through features extracted from X-ray radiographs. The proposed method, which can improve the diagnosis of CS,

Table 6: Evaluation about SCS.

| | Gold standard | |
|---|---|---|
| | SCS | Non-SCS |
| Testing results | | |
| SCS | 28 (TP) | 52 (FP) |
| Non-SCS | 7 (FN) | 213 (TN) |

Table 7: Testing results: accuracy, sensitivity, and specificity.

| Types | Accuracy | Sensitivity | Specificity |
|---|---|---|---|
| CSR | 75.00% | 74.87% | 75.23% |
| CSM | 79.33% | 77.78% | 79.61% |
| VACS | 77.00% | 80.56% | 76.52% |
| SCS | 80.33% | 80.00% | 80.38% |

combining fuzzy calculation extracted schemes is developed with the target of reducing the subjectivity in the aspect of visual interpretation of X-ray image by clinicians. Later, the fuzzy calculation can be embedded into automatic recognition program to form CAD expert system platform for the diagnosis of CS.

## 7. Conclusions

This paper showed a fully preliminary fuzzy calculation model to classify CS by clinical X-ray radiographs classification. The proposed method is based on X-ray radiographs ROIs selection and fuzzy calculation. The model was developed by exploring a number of clinical cases with numerous experts in orthopaedics. We extracted 10 ROIs that collectively allowed both our system and clinicians to perform making decision with high accuracy, sensitivity, and specificity.

## Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

## References

[1] H. D. Boogaarts and R. H. M. A. Bartels, "Prevalence of cervical spondylotic myelopathy," *European Spine Journal*, 2013.

[2] J. S. Butler, F. Cumhur Öner, A. R. Poynton, and J. M. O'Byrne, "Degenerative cervical spondylosis: natural history, pathogenesis, and current management strategies," *Advances in Orthopedics*, vol. 2012, Article ID 916987, 3 pages, 2012.

[3] Y. Chen, L. Xiang, J. Liu et al., "A non-opioid pathway for dynorphin-caused spinal cord injury in rats," *Neural Regeneration Research*, vol. 7, pp. 815–820, 2012.

[4] S. Matsunaga, S. Komiya, and Y. Toyama, "Risk factors for development of myelopathy in patients with cervical spondylotic cord compression," *European Spine Journal*, 2013.

[5] T. Fujimori, H. Le, J. E. Ziewacz, D. Chou, and P. V. Mummaneni, "Is there a difference in range of motion, neck pain, and outcomes in patients with ossification of posterior longitudinal ligament versus those with cervical spondylosis, treated with plated laminoplasty?" *Neurosurgical Focus*, vol. 35, no. 1, article E9, 2013.

[6] F. Yuan, Q.-C. Tan, J.-X. Zhou, and W.-B. Fu, "Investigation on the feasibility of selecting soft tissue elasticity as the objective evaluating indicator of the neck type of cervical spondylosis," in *Proceedings of the IEEE Iternational Conference on Bioinformation and Biomedicine*, 2013.

[7] Y.-Q. Sun, S. Zheng, J. Yu, K. Yan, and W. Tian, "Effect of total disc replacement on atypical symptoms associated with cervical spondylosis," *European Spine Journal*, vol. 22, no. 7, pp. 1553–1557, 2013.

[8] S. Yin, H. Luo, and S. X. Ding, "Real-time implementation of fault-tolerant control systems with performance optimization," *IEEE Transactions on Industrial Electronics*, vol. 61, no. 5, pp. 2402–2411, 2014.

[9] S. Yin, S. X. Ding, A. Haghani, H. Hao, and P. Zhang, "A comparison study of basic data-driven fault diagnosis and process monitoring methods on the benchmark Tennessee Eastman process," *Journal of Process Control*, vol. 22, no. 9, pp. 1567–1581, 2012.

[10] X. Xie, S. Yin, H. Gao, and O. Kaynak, "Asymptotic stability and stabilisation of uncertain delta operator systems with time-varying delays," *IET Control Theory & Applications*, vol. 7, no. 8, pp. 1071–1078, 2013.

[11] J. Zhang, L. Lv, X. Shi et al., "3-D reconstruction of the spine from biplanar radiographs based on contour matching using the hough transform," *IEEE Transactions on Biomedical Engineering*, vol. 60, no. 7, pp. 1954–1964, 2013.

[12] M. Hori, S. Tsutsumi, and Y. Yasumoto, "Cervical spondylosis: evaluation of microstructural changes in spinal cord white matter and gray matter by diffusional kurtosis imaging.," *Magnetic Resonance Imaging*, vol. 32, no. 5, pp. 428–432, 2014.

[13] A. Singh, H. A. Crockard, A. Platts, and J. Stevens, "Clinical and radiological correlates of severity and surgery-related outcome in cervical spondylosis," *Journal of Neurosurgery*, vol. 94, no. 2, pp. 189–198, 2001.

[14] S. Yin, X. Li, H. Gao, and O. Kaynak, "Data-based techniques focused on modern industry: an overview," *IEEE Transactions on Industrial Electronics*, 2014.

[15] S. Yin, S. X. Ding, A. H. A. Sari, and H. Hao, "Data-driven monitoring for stochastic systems and its application on batch process," *International Journal of Systems Science*, vol. 44, no. 7, pp. 1366–1376, 2013.

[16] S. Yin, G. Wang, and H. Reza Karimi, "Data-driven design of robust fault detection system for wind turbines," *Mechatronics*, vol. 24, no. 4, pp. 298–306, 2014.

[17] Q. Que, X. Ye, Q. Su et al., "Effectiveness of acupuncture intervention for neck pain caused by cervical spondylosis: study protocol for a randomized controlled trial," *Trials*, vol. 14, no. 1, article 186, 2013.

[18] R. D. Rao, B. L. Currier, T. J. Albert et al., "Degenerative cervical spondylosis: clinical syndromes, pathogenesis, and management," *Journal of Bone and Joint Surgery - Series A*, vol. 89, no. 6, pp. 1360–1378, 2007.

[19] M. McDonnell and P. Lucas, "Cervical spondylosis, stenosis, and rheumatoid arthritis," *Medicine and Health, Rhode Island*, vol. 95, no. 4, pp. 105–109, 2012.

[20] N. H. Phuong and V. Kreinovich, "Fuzzy logic and its applications in medicine," *International Journal of Medical Informatics*, vol. 62, no. 2-3, pp. 165–173, 2001.

[21] K. S. Park, Y. M. Chae, and M. Park, "Developing a knowledge-based system to automate the diagnosis of allegric rhints," *Biomedical Fuzzy and Human Sciences*, vol. 2, pp. 9–18, 1996.

[22] Y. M. Chae, I. Y. Park, and T. Y. Jang, "A clinical decision support system for diagnosis of hearing loss," *Journal of Preventive Medicine and Public Health*, vol. 22, pp. 57–64, 1989.

[23] S. K. Chung, I. Y. Park, T. Y. Jang, and Y. M. Chae, "Decision making support system in Otolaryngology—II," *Korean Journal of Otolaryngology. Head and Neck Surgery*, vol. 32, pp. 768–789, 1989.

[24] S. K. Chung, I. Y. Park, T. Y. Jang, and Y. M. Chae, "Decision making support system in Otolaryngology—III(diagnosis of allergic rhinitis)," *Korean Journal of Otolaryngology. Head and Neck Surgery*, vol. 33, pp. 104–110, 1990.

[25] Y. M. Chae, T. Y. Jang, I. Y. Park, S. K. Chung, and M. Park, "The development of a decision support system for diagnosing nasal allergy," *Yonsei Medical Journal*, vol. 33, no. 1, pp. 72–80, 1992.

[26] P. P. Smyth, C. J. Taylor, and J. E. Adams, "Vertebral shape: automatic measurement with active shape models," *Radiology*, vol. 211, no. 2, pp. 571–578, 1999.

[27] M. Roberts, T. Cootes, E. Pacheco, and J. Adams, "Quantitative vertebral fracture detection on DXA images using shape and appearance models," *Academic Radiology*, vol. 14, no. 10, pp. 1166–1178, 2007.

[28] A. Mastmeyer, K. Engelke, C. Fuchs, and W. A. Kalender, "A hierarchical 3D segmentation method and the definition of vertebral body coordinate systems for QCT of the lumbar spine," *Medical Image Analysis*, vol. 10, no. 4, pp. 560–577, 2006.

[29] S. Tan, J. Yao, M. M. Ward, L. Yao, and R. M. Summers, "Computer aided evaluation of ankylosing spondylitis using high-resolution CT," *IEEE Transactions on Medical Imaging*, vol. 27, no. 9, pp. 1252–1267, 2008.

[30] M. Cherukuri, R. J. Stanley, R. Long, S. Antani, and G. Thoma, "Anterior osteophyte discrimination in lumbar vertebrae using size-invariant features," *Computerized Medical Imaging and Graphics*, vol. 28, no. 1-2, pp. 99–108, 2004.

[31] S. Kasai, F. Li, J. Shiraishi, Q. Li, and K. Doi, "Computerized detection of vertebral compression fractures on lateral chest radiographs: preliminary results with a tool for early detection of osteoporosis," *Medical Physics*, vol. 33, no. 12, pp. 4664–4674, 2006.