# PROTOTYPE OF NMR BASED SENSOR FOR NON-DESTRUCTIVE SUGAR CONTENT MEASUREMENT IN FRUITS

Seoung In Cho and Chang Ho Chung
Department of Agricultural Engineering
Seoul National University
Suweon 441-744, Korea
E-mail : sicho@plaza.snu.ac.kr

## ABSTRACT

A 4.1MHz $^1$H Nuclear Magnetic Resonance(NMR) sensor was designed and manufactured to evaluate the internal quality of fruit. The magnet console having 963gauss magnetic field induction was used for the NMR sensor. To optimize and evaluate the NMR sensor, glycerol and sugar-water solutions were used. $^1$H(proton) resonance signals were used to estimate the sugar contents in fruits. Artificial neural network models were developed to predict sugar content in fruit from the proton resonance signals and were validated. The standard errors of predictions(SEP) were 0.565(apple), 0.394(pear) and 0.415(kiwi) respectively. The result implied that it is possible to evaluate apple, pear and kiwi into 3 grades using the NMR sensor

Keywords : NMR, sugar content, neural network, resonance signal, apple, pear, kiwi

## INTRODUCTION

Recently customers' criterion of selecting fruits do not depend on the basis of outer features any more but on the basis of inner properties such as sugar content(SC) and freshness. The quality of fruits has been decided by species, shape, size and color, however these criterion were not confined completely. In Korea, after selecting sample fruits in total fruits, the SC of fruits has been determined by a reflection SC meter destructively. However it takes time to determine SC, it is just represent a clue of SC of the total fruits. Therefore, the researches for individual measurement of SC in fruits are necessary for quality classifications.

The researches for determining internal qualities have been conducted since 1970. Recently, the many researches of nondestructive measurement using the properties of light, X-ray, ultrasonic, NIR and NMR are being conducted in the world.

NMR measurement has good merits against other methods. The NMR measurement are less affected by the size, density, color, mass, homogeneity and damage of samples, and it can measure several times at the same samples. The NMR can be used in determining moisture content, fat content, and sugar content with appropriate signal processing techniques.

Cho et al.(1991) measured the SC using a 200MHz high resolution NMR. He enhanced the resolution of measurement of SC to 1.8% in water and sugar solutions. He used inversion recovery pulse technique for the experiment. Ray and Krutz(1993) measured the mass and the SC of cherry using a 5.35MHz NMR. They developed a SC measuring model using spin echo variables, and r values of the mass and the SC model were 0.98 and 0.95 respectively. Zion et al.(1993) used a 85.5MHz NMR for measuring SC of prunes. They used a 20mm surface coil to get NMR signals, and made an analysis of the NMR spectrum. The r value of the model was 0.907. Stroshine et al.(1994) measured the SC of apple, orange, and tomato using a 5.35MHz NMR. They used spin echo ratio and made a SC measuring model. The $r^2$ values of the model were 0.84(apple), 0.67(orange) and 0.33(tomato) respectively. Cho et al.(1990) developed a permanent console design simulation program for a NMR ripeness sensor. He designed a low resolution magnet console using FEA method and evaluated it.

The model of neural network has a capacity of self studying, and can represent a nonlinear function with insensitivity to noise. In this study, neural network was used for measuring the SC of fruits.

The goal of this study is to develop a low resolution pulsed NMR sensor to measure the SC of fruits using artificial neural network.

## MATERIALS AND METHODS

### Samples

Sugar-water solutions and fruits samples were used. The number of Sugar-water solutions was 14 and its SC ranged from 3 to 27% with 2-3% differences. Sugar-water solutions were poured in a glass vial whose diameter was 30mm and whose length was 200mm. Fruits used for NMR experiment were apples, pear and kiwi.

**NMR system**

The NMR system was consisted of a RF signal generator, a Pulse Programmer(PPG), a RF Amplifier, Probe, Digitizer, and Magnet Console.

A block diagram of the system is shown in Fig. 1. The resonance circuit was composed of a serial resonance coil and a vacuum capacitor whose value could be variable to 125pF. Diameter and length of the resonance coil was 60 mm, and 120 mm respectively. #14 copper wire was used for the coil. Inductance of the coil was 10.7 $\mu$H. The designed magnet console is shown in Fig. 2. The strength of magnet console was 963 gauss, and the operating RF resonance frequency was 4.1MHz. A permanent magnet has the characteristics of losing the strength -0.19 %/℃ in ceramic type magnet material. To keep the strength of permanent magnet constantly, a temperature control box was designed(Fig. 3). The temperature was controlled within $\pm$ 0.1℃ and the variance of the magnetic field strength was within $\pm$ 0.2 gauss. The magnet console was insulated and closed except its center, where the samples were placed.

## RESULTS AND DISCUSSIONS

**System optimization**

To optimize the NMR system, a glycerol sample in a glass vial was used. After the system turns on, the exact resonance condition was found by trimming the vacuum variable capacitor. The signal at resonance was shown in Fig.4. The time base of an oscilloscope was 10$\mu$s and 8,192 data were gathered for 1.6 msec. The acquired signal was a simple FID(Free induction decay) signal. Because the acquired signal was oscillated, an envelope signal was acquired by averaging the FID signals for 3 seconds. Fig. 5 showed that the measurable signal started to be appeared about 50$\mu$s. Before 50$\mu$s, there were two types signals : pulse width(12$\mu$s) for FID and the dead time of coil. The envelope of acquired signal has a characteristics of decaying according to exponential function. The time constant $T_2^*$ could be obtained as following equation.

$$A = A_0 \, \mathrm{Exp}(-t / T_2^*) \tag{1}$$

A = Acquired signal amplitude at time t

$A_0$ = The max. amplitude of signal

**Experiment with sugar-water solutions**

After optimizing the NMR system, experiments with sugar-water solutions were conducted(Fig. 6). To find the clues of SC measurement, the ratio of two FID voltages were selected. After FID voltage $V_1$ at 100us and $V_2$ at 150us were selected, the ratio was computed by dividing $V_1$ by $V_2$. The SC can be calculated from the equation $SC = K \cdot V_1/V_2$. This variable predicted the SC of sugar-water solutions better than any other ratios. The $r^2$ value was 0.972(Fig. 7)

**Experiment with fruits**

The envelopes of water, kiwi, apple are shown in Fig 8. Envelopes were different among them. Fruits have water, sugar, solid and other composition in them unlike a liquid sugar-water solution. Therefore, the variable acquired sugar-water solution could not predict the SC of fruits. Because the resonance signal acquired from fruits has a few $T_2^*$ value responding on its compositions, it is possible to suppose that the relation between SC and the resonance signal is nonlinear. To find proper ratios from 100us to 150us, SAS Package was used. 4 ratios with 8 voltages at different times were selected for predicting SC of apples and kiwi. 7 ratios were selected for SC of pears. Ratios of each fruit were different. Selected ratios were used as input values of neural network model. Neural network(NN) model was a 3 layer perceptron, and back-propagation training method was used. The number of training was 20,000 respectively.

The SC of fruits was measured using a digital refractometer. The measured part of fruits was the center of samples and two SC data were averaged.

**1) Experiment with apple**

The number of samples was 30. To minimize the difference of mass, the mass of each samples was prepared in 25.5g ±0.2g. The SC of apples ranged from 10.6% to 16.0%. To predict SC of apples, NN was used. The number of input nodes, hidden nodes and output node was 4, 4, and 1. 20 of 30 samples were used to train, others were used to validate the NN model. Fig. 9 shows that the result of validation. The $r^2$ value and the SEP for the validation were 0.902 and 0.565 respectively.

**2) Experiment with pear**

The number of samples was 20. To minimize the difference of mass, the mass of each samples was prepared in 40.4g ±0.2g. The SC of apples ranged from 9.6% to 13.1%. To predict SC of apples, NN was used. The number of input nodes, hidden nodes and output node was 7, 4, and 1 respectively. 12 of 20 samples were used to train, others were used to validate the NN model. Fig. 10 shows that the result of validation. The $r^2$ value and the SEP of validation were 0.924 and 0.394 respectively.

**3) Experiment with kiwi**

The number of samples was 13. Whole fruits were used to acquire the FID signals. Because the diameter of probe was 60mm, normal size of kiwi could be placed in the probe coil(fig 11). The SC of apples ranged from 8.7% to 12.2%. To predict SC of apples, NN was used. The number of input nodes, hidden nodes and output node was 4, 4, and 1. 8 of 13 were used to train, others were used to validate it. Fig. 12 shows that the result of validation. The $r^2$ value and the SEP of validation were 0.905, 0.415 respectively.

## CONCLUSIONS

A 4.1MHz $^1$H NMR sensor was designed and manufactured to evaluate the SC of fruits nondestructively. After optimize NMR system with a glycerol sample, experiments with sugar-water solutions were conducted. The value for predicting SC of sugar-water solutions was the ratio between two voltages of the NMR resonance signal at different times. The $r^2$ value was 0.972. The experiments with apple, pear, and kiwi were conducted. To predicted SC of fruits, artificial neural network was used. The SEPs of validation of apple, pear, kiwi were 0.565, 0.394, and 0.415 respectively. This results show that it is possible to evaluate apple, pear, and kiwi into 3 grades using the pulsed proton NMR sensor.

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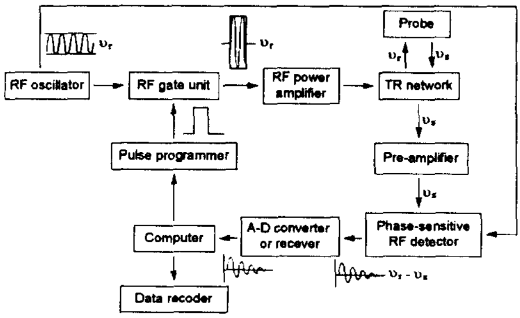



Fig. 1 Schematic diagram of the [1]H NMR sensor

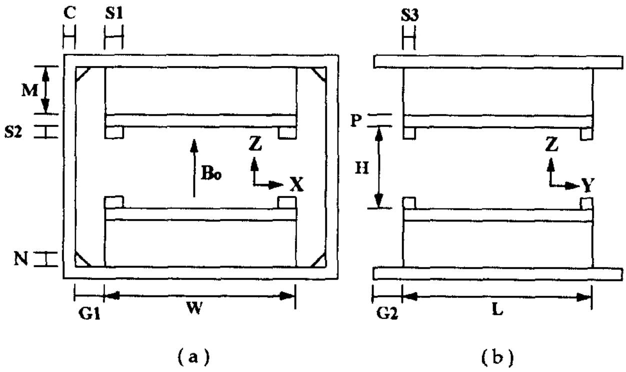



Fig. 2 Permanent magnet console for the NMR sensor

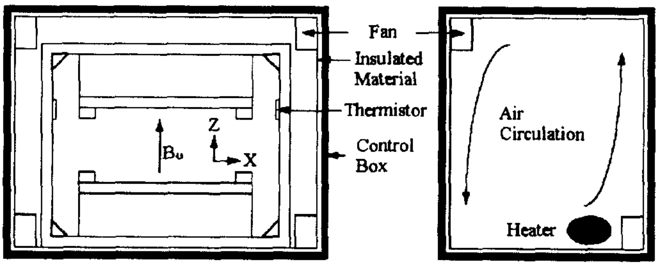



Fig. 3 Temperature control box for the permanent magnet

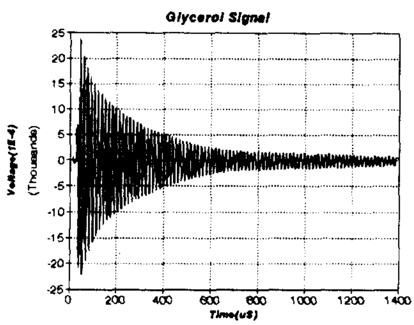



Fig. 4 Resonance signal from glycerol

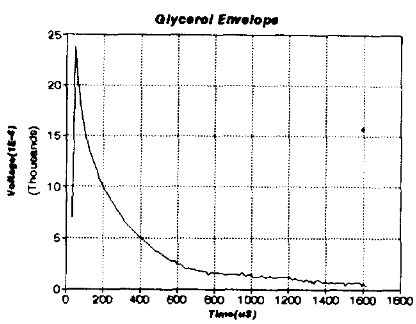
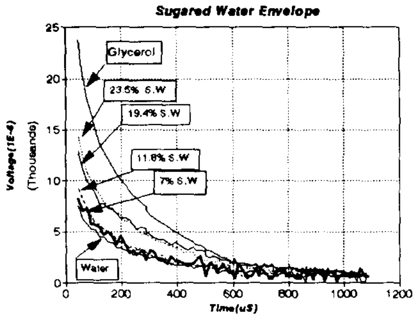



Fig. 5 Envelope of the glycerol resonance signal



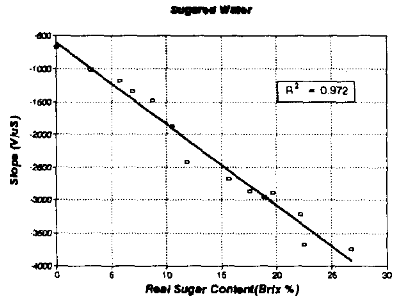




Fig. 6 Comparison of exponentially decayed signals from several sugar-water solutions

Fig. 7 Correlation between slope and sugar content

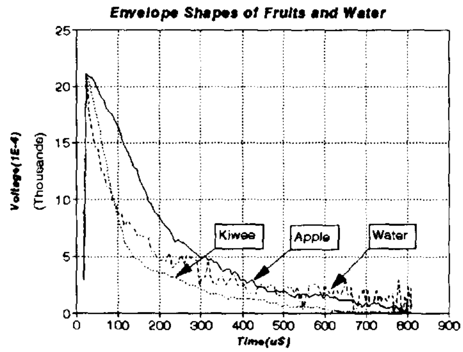



Fig. 8 Comparison of the envelopes from water, apple, kiwi samples

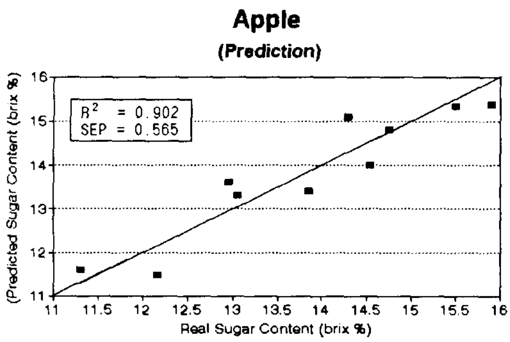



Fig. 9 Prediction of sugar content in apple using Multi-Layer Perceptron Neural Network(MLPNN)

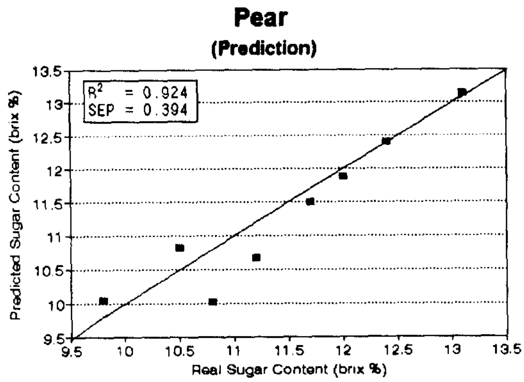



Fig. 10 Prediction of sugar content in pear using MLPNN

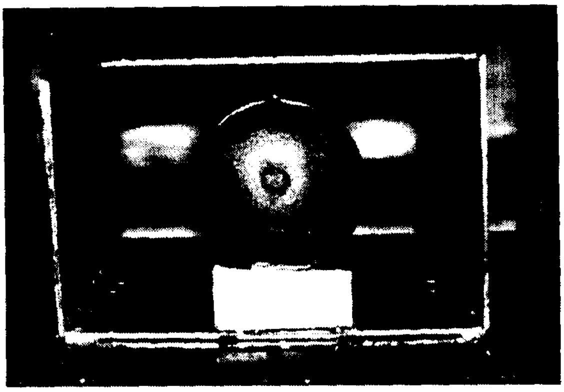


Fig. 11 A kiwi sample in the probe coil

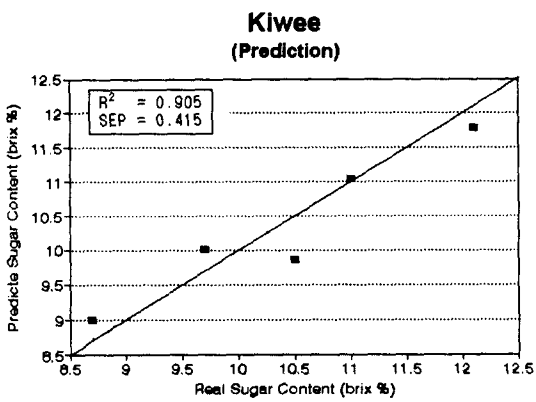



Fig. 12 Prediction of sugar content in kiwi using MLPNN