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Development of a MEMS Accelerometer based Hand Tremor Stabilization Platform

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Abstract—*This paper deals with real time development of cost effective self stabilizing spoon for patients with Parkinson's disease using wearable MEMS tri-axial accelerometer. In this proposed model, we designed MEMS accelerometer in FEM based Multiphysics simulation software with an easy to adopt without the help of any trained classifier for identifying the hand tremors in a Parkinson's disease patient. This proposed system is build around an AVR microcontroller along with a 3 DOF (Degree of Freedom) tri-axis IMU (Inertial Measurement Unit) in a form of hand held hardware. The patient's hand tremors are read by the system in form of acceleration data which is fetched from the IMU, an embedded 6-point calibration filter performs estimation on the data acquired. The output from the said filter is then used to drive a spoon connected to a 9gm servomotor. The rotational direction of servomotor is opposite to that of the tremor signal, these helps to stabilize the spoon. Thus, accelerometer based self stabilizing spoon not only reduces the complexities in Parkinson's patient life but presents as a cost effective device that has minimized power consumption (<13.5mW) by associated circuitry covering small size (3.9mm*4.0mm*4.1mm) thus enabling mobility.*

1. INTRODUCTION

Parkinson's disease is a persistent and progressive movement disorder, affecting 3% of the population over the age of 65 years and leaving them to experience a broad range of symptoms. Parkinson's involves malfunction of neurons in an area of the brain called the substantia nigra which produce a chemical material (dopamine) that helps nerve cells to communicate [1]. The motor symptoms of the Parkinson's disease are hand tremor, bradykinesia, rigidity and impair postural balance [4][5]. The frequency range of hand tremor falls in range of 4Hz to 6Hz [1]. The patients suffering from hand tremor of Parkinson's disease are unable to do their normal work. The main problem faced by the patient with Parkinson's disease is while eating their food. This paper deals with a real time development of accelerometer stabilized spoon which enable the Parkinson's disease patients to have their food without any hindrance. The proposed system consists of a three axis MEMS accelerometer (MPU6050) which detects the direction and acceleration of hand tremor. A low power microcontroller determines the stage of the tremor and drives a spoon connected to a 9gm servomotor. The rotational direction of the 9gm servomotor is opposite to that of the detected hand tremor, these helps to stabilize the spoon. The on board processor uses two bidirectional i^2c based open drain Serial Data Line (SDA) and Serial Clock Line (SCL), internal bus lines to communicate with the MEMS accelerometer, the PWM register and the servomotor for driving the motor. The entire paper is divided into following parts, where section 1 introduced the work. Section 2 describes the mathematical model of the designed spoon. Section 3 describes the mathematical modeling of filter. Section 4 expose the methodology used to develop the designed hardware and finally section 5 describes the conclusions and future works of the proposed system.

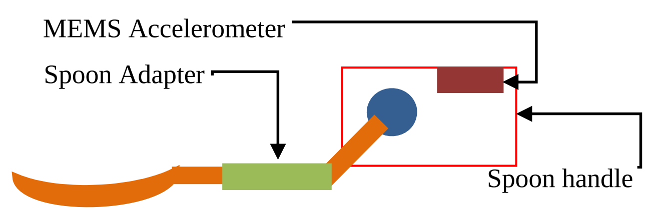

Fig. 1 The block diagram of developed self stabilizing spoon

2. SYSTEM MODELING

In order to develop the proposed system, first we have considered designing the MEMS sensor followed by development of the mathematical and consequently the error model of the accelerometer for optimizing the position error during installation.

Mathematical Model of MEMS Accelerometer

MEMS accelerometer consist of a proof mechanical mass etched over silicon wafer that acts as a mechanical suspension. Figure 2 illustrates the equivalent mechanical mass damper.

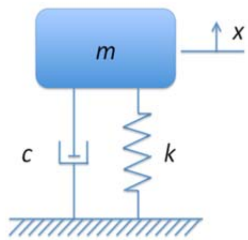

Fig. 2 Mass damper equivalent of MEMS accelerometer

The application external disturbance F(t), displaces the proof mass from the spring arrangement by x(t) amount. The entire system can be represented by Eq.1.

$$\acute{x}(t) + \frac{c}{m}\acute{x}(t) + \frac{k}{m}x(t) = 0 \quad (1)$$

Where, B (N-s/m) is damping coefficient, k (Nm) is the spring constant and m (Kg) is mass of the load.

Error Model of MEMS Sensor

The accelerometer's measurement accuracy can be improved through calibration of the sensor's output [4, 5]. The most common method is the maximum and minimum method, but this analogy can only estimate the scale factor error and bias, and is susceptible to the influence of random errors. Figure 3 shows the output from the MEMS accelerometer.

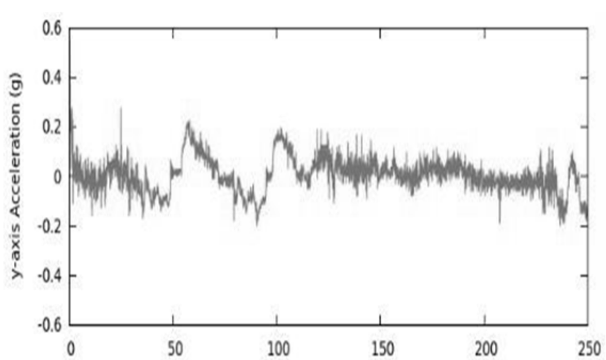

Fig. 3 The output acceleration data from the MEMS sensor

Basically, the error analysis of the MEMS accelerometer in wearable applications is done based on these factors, i) accelerometer bias, ii) installation error and iii) gain factors. According to the characteristics of the measurement error, the MEMS accelerometer error model [6, 7] in a wearable device is given by Eq.2 [6,7].

$$\begin{bmatrix} h_x \\ h_y \\ h_z \end{bmatrix} = \begin{bmatrix} b_x + n_x \\ b_y + n_y \\ b_z + n_z \end{bmatrix} + \begin{bmatrix} S_x & -a_4 S_y & -a_5 S_z \\ a_1 S_x & S_y & -a_6 S_z \\ -a_2 S_x & a_3 S_y & S_z \end{bmatrix} \begin{bmatrix} g_x \\ g_y \\ g_z \end{bmatrix} = \begin{bmatrix} b_x + n_x \\ b_y + n_y \\ b_z + n_z \end{bmatrix} + \begin{bmatrix} S_x & K_{12} & K_{13} \\ K_{21} & S_y & K_{23} \\ K_{31} & K_{32} & S_z \end{bmatrix} \begin{bmatrix} g_x \\ g_y \\ g_z \end{bmatrix} \quad (2)$$

3. SYSTEM OVERVIEW

Sensor Noise Reduction Algorithm

The equations of X-axis are Eq.3 and Eq.4

$h_{x1}=b_x-K_{12}, h_{x2}=b_x-K_{13}, h_{x3}=b_x+S_x$ (3)

$h_{x4}=b_x+K_{12}, h_{x5}=b_x-S_x, h_{x6}=b_x+K_{13}$ (4)

The equations of Y-axis are Eq.5 and Eq.6

$h_{Y1}=b_Y-S_y, h_{Y2}=b_Y-K_{23}, h_{Y3}=b_Y+K_{21}$ (5)

$h_{Y2}=b_Y+S_y, h_{Y5}=b_Y-K_{21}, h_{Y6}=b_Y+K_{23}$ (6)

Similarly, the equations of Z-axis are Eq.7 and Eq.8

$h_{z1}=b_z-S_Y, h_{z2}=b_z-S_z, h_{z3}=b_z+K_{31}$ (7)

$h_{z4}=b_z+K_{32}, h_{z2}=b_z-K_{31}, h_{z6}=b_z+S_z$ (8)

The above equations can be summarized as Eq.9, Eq.10 and Eq.11

$4b_x= h_{x1}+h_{x2}+h_{x4}+ h_{x6}$, $2S_x = h_{x3}-h_{x5}$, $2K_{12} = h_{x4}-h_{x1}$, $2K_{13} = h_{x6}-h_{x2}$ (9)

$4b_Y = h_{Y2}+h_{Y3}+h_{Y5}+ h_{Y6}$, $2S_x=h_{Y4}-h_{Y1}$, $2K_{21}=h_{Y3}-h_{Y5}$, $2K_{32}= h_{Y6}-h_{Y2}$ (10)

$4b_z = h_{z1}+h_{z3}+h_{x4}+ h_{x6}$, $2S_z= h_{z6}-h_{z2}$, $2K_{31}= h_{z3}-h_{z5}$, $2K_{32}= h_{z4}-h_{z1}$ (11)

The MEMS accelerometer calibration arrangement using six-point analogy [8, 9] is shown by Fig.4 and Table.1 data read from the sensor.

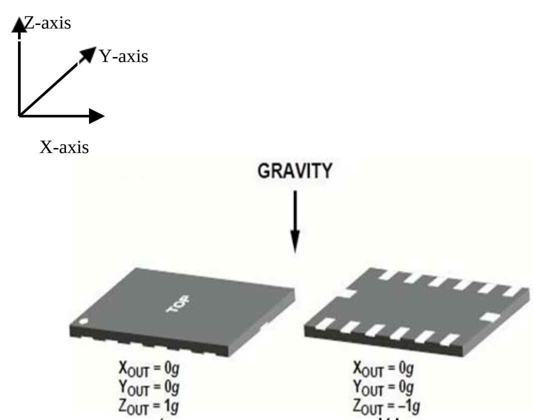

Fig. 4: Sensor calibration arrangement for Z-axis
a) Inverted (-1G) b) Not inverted (+1G)

The sensor output for 0g corresponds to 512 read out from the sensor's 10 bit ADC (Analog to Digital Converter), the zero-G (m_z) and the sensitivity (∂_z) values for Z-axis of the MEMS accelerometer are shown by Eq.12 and Eq.13

TABLE I: SENSOR CALIBRATION DATA FOR Z-AXIS NON-INVERTED AND INVERTED

Sample No.	Accelerometer Values NON-INVERTED			Sample No.	Accelerometer Values INVERTED		
	X axis	*Y axis*	*Z axis*		*X axis*	*Y axis*	*Z axis*
1	512	511	619	1	514	513	419
2	511	513	617	2	513	512	417
3	512	512	618	3	512	513	418
4	513	512	619	4	511	512	419
5	512	511	617	5	513	511	417
6	511	513	616	6	511	512	416

$$m_z = (618+413)/2 = 515.2 \tag{12}$$
$$\partial_z = (618-413)/2 = 102.5 \tag{13}$$

The six-point calibration process applied to the other two axis of the accelerometer, the coefficients of the error model can be written as shown in Eq.14 as the

$$\begin{bmatrix} g_x \\ g_y \\ g_z \end{bmatrix} = \begin{bmatrix} 1.02 & 0.02 & 0.00 \\ 0.08 & 1.01 & -0.09 \\ -0.02 & 0.16 & 1.00 \end{bmatrix} \begin{bmatrix} h_x + 11.06 \\ h_y - 0.20 \\ h_z - 31.09 \end{bmatrix} \tag{14}$$

The corrected acceleration values of three spatial orthogonal axes [10] in each hand movement are measure in a certain sampling frequency, the vectors can be represented as by Eq.15

$$G=(g_x, g_y, g_y) \tag{15}$$

Where $g_T = (g_T^0, g_T^1, \ldots \ldots \ldots, g_T^{L-1})$, T=x, y, z are the corrected acceleration vectors and L is length of the sequence.

4. REAL TIME IMPLEMENTED HARDWARE

The output from the MEMS accelerometer is shown by Fig. 3 in section 2.2. Figure 5 shows the filtered signal form the IMU. The general block diagram of the designed wearable device is shown in Fig.6.

The real time implemented device comes as a hand held device, with the tri-axial MEMS accelerometer MPU6050 mounted on the handle of the spoon. An on-board processor, Atmega 328 reads the accelerometer data and sends it over to the servo actuator.

The on board processor uses two bidirectional I^2C (Inter-Integrated Circuit) based open drain Serial Data Line (SDA) and Serial Clock Line (SCL), internal bus lines to communicate with the slave MEMS peripheral sensor in Fig.6.

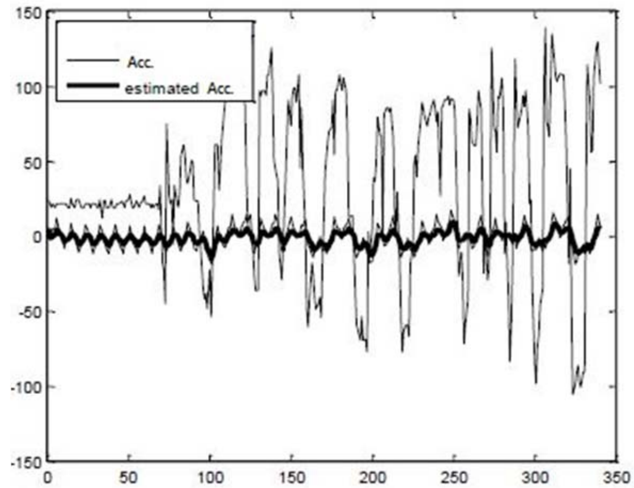

Fig.5 Estimated acceleration from the MEMS sensor

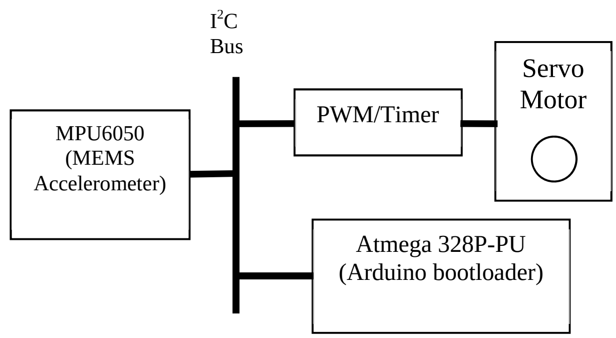

Fig.6 Internal connection bus diagram of the hand held self stabilizing spoon

5. CONCLUSION

In our present work, the proposed hand held self stabilizing device consists of a MEMS accelerometer system which generates a stream of acceleration data for the hands tremors recorded in Parkinson's disease patients. The analysis on acceleration data is done on the device itself which is then used to actuate the servo motor. The real time implemented hardware is shown in Fig.7. The developed MEMS based self stabilizing spoon is largely different from the current and existing solutions which involve the use of devices that are generally bulky and painful to use. Some such solutions also make use of non-standard cutlery which not that easy to obtain. Moreover, the developed device has a spoon adapter and so can be used with every kind of cutlery.

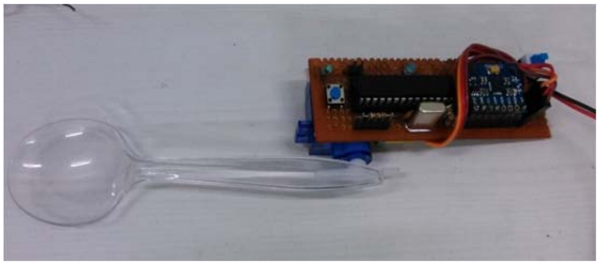

Fig.7 The real time implemented of accelerometer based self stabilizing spoon

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