A sensor-based Glove interaction for nursing care Robot assistance

[1]**Prof. V. Sujatha**, Dean, & Professor,Department of OBG Nursing, Sri Venkateswara College of Nursing, Chittoor – 517127, AP
[2]**Prof. Edna Sweenie J**, Deputy Director & Professor, Department of Child Health Nursing, Sri Venkateswara College of Nursing, Chittoor – 517127, AP
[3]**T. Gayathri,** Professor Department of Medical Surgical Nursing, Sri Venkateswara College of Nursing, Chittoor – 517127, AP
[4]**S. Sujitha**, Associate Professor Department of Child Health Nursing, Sri Venkateswara College of Nursing, Chittoor – 517127, AP
[5]**C. Vasantha Kumari**, Assistant Professor Department of Medical Surgical Nursing Sri Venkateswara College of Nursing, Chittoor – 517127, AP

Abstract- Between 2015 and 2050, the World Health Organization predicts that the number of old people would quickly increase. Population ageing is leading to an increase in physical disabilities and mobility issues. There is a significant opportunity to improve healthcare delivery by using assistive robots, which are constantly improving robotic technology. Robotic technologies for the care of the elderly and handicapped are thus becoming more relevant. In an assistive robotic system, a sensor glove for human-robot interaction is conceived, manufactured, and assessed in this article. Flex sensors and an inertial measurement unit (IMU) are used to detect the user's finger motions and additional off-the-shelf electrical components are employed in the sensor glove. It is the primary objective of this study to make human-assistive robot interaction more intuitive and dependable. As a result, this study focuses on three key topics: 1) developing a pattern for these kinds of sensor gloves, 2) testing the performance of sensor gloves with the use of flexible sensors, and 3) examining how to analyse systems with a person in the loop while using a sensor glove. Using this design pattern, the sensor glove can be a reliable interface for operating the assistive robotic system, according to our experiments. Aside from that, our estimate approach may be used to the study of an assistive robotic system with a person in the loop, allowing us to theorise about the system's optimal parameters.

Keywords— nursing-care assistive robotics, sensor glove,human-robot interaction, human-in-the-loop system.

I. INTRODUCTION

Between 2015 and 2050, the World Health Organization predicts that the number of individuals aged 60 and older would climb from 900 million to 2100 million. The ageing population is leading to an increase in the number of people who are physically disabled or have mobility issues. As robot technology continues to advance, assistive robots have the potential to extend healthcare services to solve the following issues.

In order to operate assistive robots remotely, gesture-based human-robot interfaces are a simple and intuitive [2] option. There are three basic ways to implement gesture-based interfaces: image-based, glove-based, and non-wearable techniques. Non-wearable techniques have a lower resolution than others. Some researchers [4] have used image-based approaches to operate an assistant robotic system. This means that image-based approaches rely heavily on lighting conditions and surroundings [5]. With these limitations, glove-based solutions are more accurate and dependable in the application of homecare robot control when dealing with changing lighting conditions and complicated human environments. Flex sensors and inertial sensors [6] were employed in our study because they are often used in glove-based systems for detecting static finger bend and dynamic [4] arm movement.

The development of smart gloves with sensors and electrical devices has been a major focus in recent years. To develop a smart glove (HandiMate) that serves as an input device for self-configurable modular robots, a combination of flex sensors and inertial sensors is used. Ziro and other commercial items of a similar kind exist. There have also been investigations on the manufacturing process and characteristics of piezoresistive strain sensors [8]. Besides modular robotics, we designed a number of subsystems that will be detailed in this study, as well. The sensor glove and the whole robotic system will be tested in Section III. Here, we'll explore the system's dependability and accuracy, which were addressed in the preceding sections. Section V concludes the essay. sensor glove that can record both static finger motions and dynamic arm movements. rable sensor glove A prototype nursing-care robotic system including the glove and an Automated Guided Vehicle (AGV) and a commercially available robot has been developed (YuMi). The following is a list of the issues we considered in our research: There is a new design pattern for this kind of sensor glove, and we first looked at it. As a follow-up, we devised a new way to assess the performance of sensor gloves using flex sensors. Three methods for human-in-the-loop system analysis were developed and assessed, one of which included using the sensor glove.

Here's how the rest of the article's sections are organised:

Section II explains the general design of the wearable sensor glove and the nursing-care robot. Sensor gloves were then used in a variety of disciplines, including health care [9], sign language comprehension [8], virtual reality [10], and more.

However, the entire performance of the complete glove system (sensors, electronics, and robotic systems) is seldom formulated by researchers [6]. Even though commercially available smart gloves can be used to control modular robots and virtual reality, studies on applying smart gloves in controlling nursing care robotic systems are of great value, despite the fact that performance specifications for sensor gloves are entirely different from one application to the next, resulting in important issues when trying to match a glove to a specific application. In addition, nonlinear behaviour and reaction times of around 200 ms are common in resistive sensors [11]. Sensor glove systems may become unstable as a result. A performance assessment index should be implemented as a consequence.

II. SENSOR GLOVE

A *Overall Architecture*

YuMi robot placed on AGV has two subsystems. YuMi is a manipulative device created to assist those who have difficulty using their upper limbs. People with lower limb disabilities need to be able to move, and the AGV helps them do so.

As a human-robot interface device, our sensor glove is developed so that users may naturally manage the assistive robotics system. Eight-finger signals may be translated into AGV movement orders and mode switch commands using the glove, as demonstrated in Figure 1.

When the user moves their arm in 3-D, the YuMi can read that movement and translate it into orders for the robot. Gesture-based human-robot interfaces are governed by standards issued by the British Standards Institution (BSI) and the International Standard Organization (ISO). Gesture signs, for example, have taken some of these suggestions into account throughout the design process.

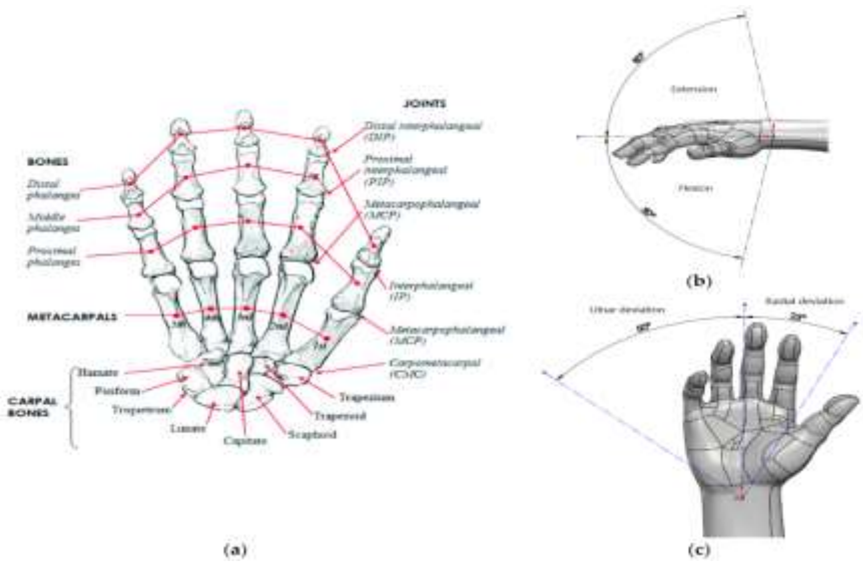

Figure. 1. Fingers and arm gesture representations of the user the robotics system's data and command flow. Schematic of a robot

The following is a breakdown of the steps involved in an interaction: Flex sensors placed in the glove at the user's metacarpophalangeal joints (bent or straight) are also detected by the inertial measurement unit (IMU) linked to the wristband, which measures motion. 2) As shown in Fig. 2, the voltage signals are delivered to a microcontroller. The motions of fingers and arms are identified and categorised into predetermined models using threshold judgement and decision tree classification techniques of classification. Assistive robotic systems' control boards get the appropriate Bluetooth instructions. For the glove system, HC06 was selected because of its small size, high data rate, and low price. AGV or YuMi will then reply in accordance with the current mode of the system (which may be switched back and forth using mode switch instructions).

Figure 2 depicts the sensor glove's circuit design in more detail. It may be broken down into five distinct sections based on its intended use:

- Finger gesture recognition circuit (flex sensor 2.2)
- IMU unit (MPU6050)
- Arduino Mega (microcontroller)
- 9V zinc-manganese dry battery
- Bluetooth unit (HC06)

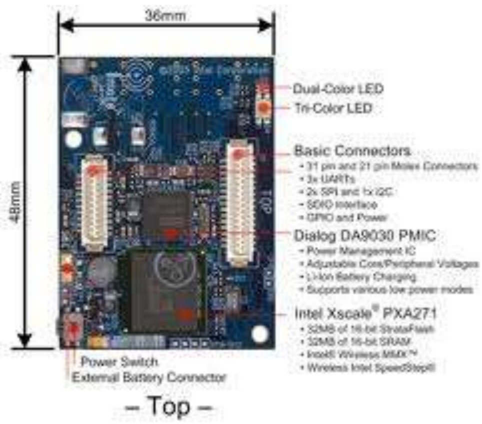

Figure. 2. Sensor glove circuit design

B *Finger Bend Detection Subsystem*

Finger gesture identification relies on the resistance-strain effect, which occurs when a certain motion is performed on the backs of flex sensors inserted in the matching fingers. Measurement of voltage is done using an analog-to-digit converter (ADC) and an adjustable resistor. Next, the resistance of flex sensors is calculated using Kirchhoff principles.

Thus, the "angle-resistance" curve may be determined in advance, and the gesture of fingers (angle of metacarpophalangeal joints) can be derived from this data.

To send a command to an assistive robotic system through Bluetooth, an AGV's omnidirectional movement command may be created using the matching gesture table illustrated in Fig. 1. The mechanical nature of human hands restricts the number of possible finger combinations to a maximum of 32. Only eight of these variables are examined in this study.

C *Arm Movement Detection Subsystem*

A four-stage model [14] may be used to represent the whole arm movement detection process:

Creating and transmitting a signal segmentation and processing of the input signals, and the extraction of feature information The use of pre-trained decision trees for classification Transmission of a YuMi manipulation command

In order to track the movement of the user's arm, we connect an IMU MPU6050 to the wristband. A Digital Motion Processor, a 3-axis gyroscope, and a 3-axis accelerometer make up the MPU6050 (DMP). The serial port may be used to send motion data in the form of 9-axis motion information. MATLAB programme will evaluate the data that is delivered to a computer through Bluetooth from the IMU. Afterwards, a 35 Hz low-pass filter is applied to the original signal to smooth it out. The cut-off frequency was determined by experiments in the 020Hz frequency range, which is the range in which human motion occurs. For the next step, we utilise the Sliding Window Method to segment the signal, which has a duration of 4.5 seconds and an overlap ratio of 20% since the movement is steady and there are little fluctuations. There are six attributes that may be used as features for classification: max/min/average/no. of peaks/variance/standard deviation of yaw/roll signal. We utilised 240 samples to build the decision tree in the course of preparation work (training model). The retrieved characteristics will be utilised to categorise various movements of the user's arm throughout the robotic control procedure. As a result, YuMi will carry out the instructions that were sent to the robotic control board through Bluetooth.

D *Affiliated Electronic Components*

The Arduino Mega is a good choice for this sensor glove project because of its size and capabilities. There are 54 general-purpose digital I/O pins.

Serial communication, which is utilised for Bluetooth in this application, is supported by some of the pins. The quantization error is kept to 4.9mV thanks to the 16 10-bit analogue to digit converters for 05V input. In addition to it, an ATmega2560 CPU with a maximum clock rate of 16 MHz is used. This processor may be used to detect arm and finger motions, categorise them into multiple models, and deliver instructions in this particular application.

Because it's so inexpensive, the Arduino Mega can be easily expanded. We were able to create the glove's functionality more quickly because to the inclusion of open-source tools like the serial communication library.

For a variety of reasons, Bluetooth is the preferred method of communication between the sensor glove and robots. When it comes to indoor assistive robot control, it has a communication range of 10 metres. It has a maximum of 8 devices per network, which is sufficient for the purpose at hand. In addition, Bluetooth's 1 Mbps data throughput, cheap cost, low power profile, and great adaptability make it an excellent option for this application.

There is a 9-volt dry battery linked to the wristband to power the Arduino Mega, Bluetooth, and IMU components. In the meanwhile, a rather steady reference voltage is generated for the finger bend detecting subsystem using a voltage regulator module MC33269 (included into Arduino Mega).

E *Performance Evaluation Index*

Sensor glove stability is influenced by a variety of reasons, including changes in the reference voltage, discrepancies between nominal and real resistor values, quantization errors, and variations in the sensitivity of the flex sensors due to fatigue. Flex sensor error, embedded system error, and measurement error are all examples of these problems. Flex sensor error may be measured and will be detailed later in the experiment. The specifications of electronic components may be used to predict embedded system errors and measurement errors.

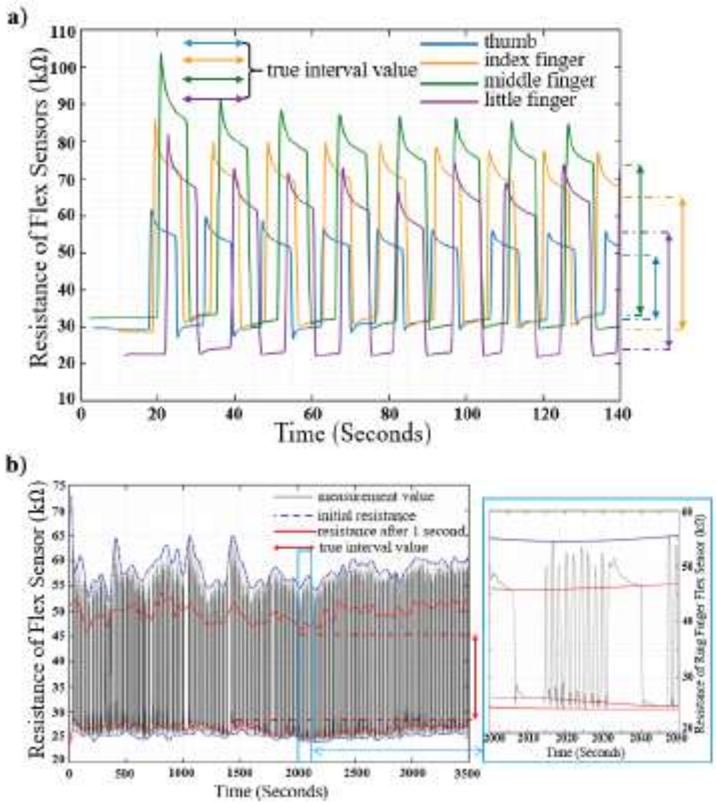

Figure. 3. (a) Resistance of flex sensors corresponding to thumb, index finger, middle finger, and little finger while performing periodic bent/straight motions. To measure static state resistance, bend/straighten the flex sensor ring finger 1000 times and measure the resistance.

Fig. 3 (a) depicts the change in nominal value of flex sensors' resistance produced by varied sensor characteristics and different attachment locations. Sensor interval ranges were 3250 k3067 k3475 k2557 k, correspondingly, for the thumb, index finger, middle finger, and little finger. We are solely interested in the two states of fingers that are totally straight and bent in this study. For this reason, it is only measured and used in these two static states.

$$U_{nominalout} = \text{quantization}\left[\frac{U_{ref}}{R_{btrue}+R_{ref}} R_{ref}\right] \qquad (1)$$

As seen in Equation (1), this voltage may be utilised to determine the position of the fingers. It may be calculated using the voltage law of Kirchhoff. Because of different mistakes and disturbances in the measurement process, such as variances between nominal and real values of reference resistor and reference voltage, this is not a conventional Kirchhoff's laws formulae. However, as shown in Figure 5 since we need to make sure that flex sensors as well as other electrical components do not confuse finger motions, the output voltage will be disturbed and this will decrease the range of the threshold value.

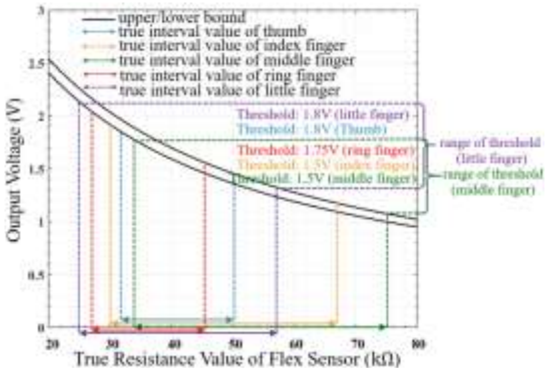

Figure. 4. True resistance of flex sensors and output voltage while considering electronic system uncertainty. The disruption of real resistance value of flex sensors revealed the impacts of sensor individual variation and sensor fatigue.

This section introduces a performance assessment index that may be used to evaluate the sensor's performance when paired with other electrical components.

Additionally, a flex sensor's best threshold value may be discovered by experimentation. To illustrate that the nominal value of an electronic component does not match its real value because of the reference voltage and resistance uncertainty, Fig. 4 demonstrates that the output voltage has upper and lower bounds that correlate to a genuine resistance value. Sensor individuality and sensor fatigue influence the genuine resistance value of flex sensors, resulting in a horizontal axis disturbance.

It is necessary to choose an adequate threshold in order to avoid misjudging the states of finger motions. The length of the range might be used as a performance assessment metric. We are less likely to confuse a bent condition for a straight one if the range is bigger. Confusion is more likely if the range is narrower or even negative in certain cases. Different reasons, such as sensor individual differences, sensor fatigue, electronic system uncertainty, etc. might be responsible for this phenomenon.

It's possible that pre-calibrated techniques like simple linear method, regression and approaches for coupling issues may enhance the performance of motion capture gloves. Instead of looking at the relationship between resistance and bend degree as a whole, this study focused only on the resistance in totally bent and straight states. TABLE I. shows that the success rate is high enough to operate the robot.

III. EXPERIMENTS OF INTEGRATED SYSTEM

A *Background, Modelling and Presumptions*

The human aspect should be included into the control loop as part of the HMI category.

Uncertain human elements are included into this assistive robotic system, making it difficult to evaluate the whole system. An analysis and forecasting model for the human-in-the-loop system is shown here. A nursing-care robotic system's ideal characteristics, such as angle velocity and acceleration, will be obtained by building a model. Robotic care for the elderly is the primary use case for this assistive robot system, which is often used in tight settings.

To achieve a good balance between accuracy and efficiency, we must consider both at the same time. With the sensor glove present, we intend to acquire the parameters in a theoretical method that can be used to a wide range of robots, and is more general than an experimental approach.

In this portion of the experiment, we examined how the sensor glove helped us steer the robot in the desired direction. We need to first modify the robot's orientation if we are going to use it in a straight tight channel, which is typical in application situations for this technology. The angle v inaccuracy should be kept to a minimum so that the route may be traversed without additional correction. The robot's size and the passage's length and breadth both have a role in determining the precise range.

The temperature limit was established at 6 degrees in this experiment.

As an ideal relay with hysteresis or dead zone, the glove subsystem (human component) is represented mathematically. This relay's threshold is determined by a random variable a, which has a zero-mean Gaussian distribution. Based on the velocity parameter v, this distribution's variance may be calculated This makes perfect sense, since increasing velocity makes it more difficult for a user to point the robot in the desired direction, and as a result, the amount of dispersion rises.

Robotic systems are predictable in compared to human behaviour. Because of this, the system's stopping distance may be described as a fixed function, stop, which is dependent on the velocity parameter.

B *Experiment Setup*

The experiment's primary assessment criteria were whether or not the robotic system could be controlled to stop in the appropriate direction using the user's finger and arm gestures.

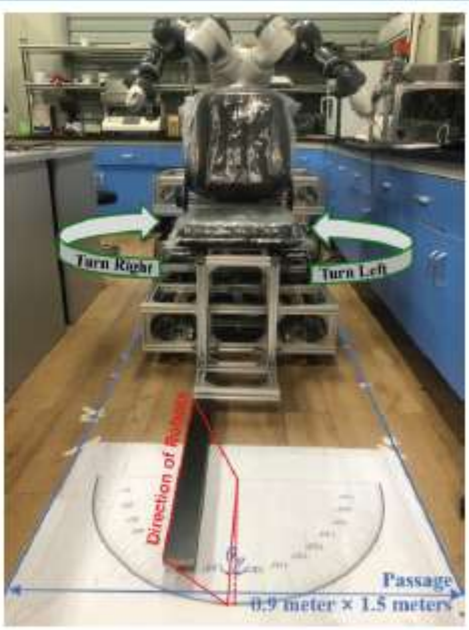

Figure. 5. Experiment setup: assistive robot rotates in the passage with length of 1.5meters and width of 0.9meter. The rotating angle is measured by a protractor printed on a paper.

Stages one and two of the experiment were separated into two. Using an illustrated gesture table, a subject wearing the sensor glove performed a series of motions at random and the success and failure rates were recorded.

Second, as seen in Fig. 5, a tunnel measures 1.5 metres in length L and 0.9 metres in width M. Passage and AGV's initial path are about 45 degrees apart. The individual utilised the sensor glove to change the robotic system's direction using varying levels of angular velocity (just the Turn Left/Right command was used). Each experiment had a predetermined angular velocity that was not affected by the joint angle.

Success and failure rates were tabulated and analysed in detail.

The successful examples are those in which the value of the stopping angle v is modest enough that the robots can travel through the passage with no additional modification. A halting angle restriction of 4 degrees to 4 degrees has been specified for this experiment based on the robot's overall dimensions and the route.

For every different parameters of angular velocity (10 rad/s, 20 rad/s, 30 rad/s), we recorded 100 set of data of stopping angle θv, respectively. The human factor (Gaussian distribution) models utilised half of the data for parameter estimation. It was then compared to actual results in order to see whether the model's predictions were accurate.

IV. RESULTS AND DISCUSSION

A First Stage: Sensor Glove

This was achieved by using the performance evaluation index approach to determine the ideal threshold value (which was first set to the centre of the range obtained in Fig. 5 and slightly altered via experiment). Figure 5 shows the final threshold values for each of the five fingers. The results \sof success rate for varied motions are presented in TABLE I.

Table I. Efficacy Of Each Gesture

Gesture	*Num of Success*	*Num of Failure*	*Success Rate*
Move Forward	48	2	96%
Move Back	47	3	94%
Move Left	50	0	100%
Move Right	50	0	100%
Turn Left	50	0	100%
Turn Right	49	1	98%
Swich Mode 1	50	0	100%
Swich Mode 2	44	6	88%

Sensor gloves may properly represent the user's intentions using the ideal threshold, as shown in this experiment's results. A technique for determining the appropriate threshold has been proven successful.

B *Second Stage: Integrated System*

We observed a succession of angular errors between the actual stopping direction and the planned stopping direction under varied commands of input velocity values vk. vi is the name of the series.

The maximum likelihood estimator is used to find a suitable value for the unknown parameters of the Gaussian distribution (the human factor). It is a technique for selecting the parameters of a distribution whose likelihood function provides the biggest value.

$$L(\mu,\sigma^2)=\prod_{i=1}^{n} f(\theta_{vi},\mu,\sigma^2)\,.$$

Using (2) to estimate the gaussian distribution with unknown mean μ and variance σ2.

$$\begin{cases}\dfrac{\partial}{\partial\mu}\ln L(\mu,\sigma^2)=0\\ \dfrac{\partial}{\partial\sigma^2}\ln L(\mu,\sigma^2)=0\end{cases}\Rightarrow\begin{cases}\hat{\mu}=\dfrac{1}{n}\sum\limits_{i=1}^{n}\theta_{vi}=\overline{\theta}\\ \hat{\sigma}^2=\dfrac{1}{n}\sum\limits_{i=1}^{n}(\theta_{vi}-\overline{\theta})^2\end{cases} \qquad (2)$$

V. CONCLUSION

Design patterns for sensor gloves that include finger gesture and arm movement sensors are presented in this study.. A robotic nursing system was used in conjunction with the glove. Using the glove developed and tested in this study, the user's intentions for controlling assistive robots were accurately reflected. After conducting an experiment and verifying the model we developed, we found that it properly predicts the success rate of guiding a robot to the intended location.

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