International Journal of Mechanical, Industrial and Aerospace Sciences
ISSN: 2517-9950
Vol:12, No:9, 2018

Hand Gestures Based Emotion Identification Using Flex Sensors

S. Ali, R. Yunus, A. Arif, Y. Ayaz, M. Baber Sial, R. Asif, N. Naseer, M. Jawad Khan

***Abstract*—**In this study, we have proposed a gesture to emotion recognition method using flex sensors mounted on metacarpophalangeal joints. The flex sensors are fixed in a wearable glove. The data from the glove are sent to PC using Wi-Fi. Four gestures: finger pointing, thumbs up, fist open and fist close are performed by five subjects. Each gesture is categorized into sad, happy, and excited class based on the velocity and acceleration of the hand gesture. Seventeen inspectors observed the emotions and hand gestures of the five subjects. The emotional state based on the investigators assessment and acquired movement speed data is compared. Overall, we achieved 77% accurate results. Therefore, the proposed design can be used for emotional state detection applications.

***Keywords*—**Emotion identification, emotion models, gesture recognition, user perception.

I. Introduction

THE integration of artificial intelligence (AI) in machines has created a better life style for humans. With the advancement in AI, the machines are being equipped with capabilities comparable to humans. An important step towards development of intelligent machines is to create a natural environment for interaction with humans. Emotion recognition is a key factor in developing an interaction between a human and a machine [1].

Our everyday behaviors are filled with expressions of our emotions that vary from facial to our body gestures. Sometimes a better understanding can be established by non-verbal cues instead of natural communication between persons [2]. However, a normal conversation between two individuals may not have a standard way of gesture expression, and the gestures can be perceived differently by different individuals [3]. Therefore, recognition of different emotions generated by a person can be a tedious job for a machine (especially without the use of AI).

In the domain of human computer interaction, there has been more focus on recognition of emotions through facial expressions, but the use of gestures for the identification of emotions remains relatively unexplored. Gestures are generally classified into three categories: adaptors, emblems, and illustrators [4]. The combined use of verbal language and hand gestures are categorized as illustrators. Adaptors are movements that a person involuntarily performs in reaction to nervousness or anxiety. Adapters can be described as fidgeting. Emblems are the hand gestures that have a specified meaning. Normally, humans rely more on facial expressions to obtain information about a person's emotions [5]. Consequently, there have been attempts to create robots capable of displaying facial emotions [6]. However, there is sufficient evidence that our posture and gestures do represent emotions correctly [7]. In order to completely understand an emotion, both the gesture and the motor expression are equally important [8].

Significant work has been done on hand gesture recognition considering its importance in human computer interaction. One approach makes use of electromyography in combination with motion detection sensors to predict gestures, while other approaches focuses on the development of algorithms to enhance the accuracy of gesture recognition [9]-[13]. Some studies have also used flex sensors for gesture recognition [14]. However, the literature lacks a conclusive work that is able to recognize and predict emotions simultaneously.

Flex sensor data provide sufficient information to classify gestures. However, translating these gestures into emotions is the current research issue. The speed of a movement has a profound effect on how it is perceived. Research shows *velocity* [15], *acceleration,* and *jerk* [16] to be reliable parameters for identifying emotions through motion kinematics. Both these parameters have been used to model machine emotions for an IGUS robotic arm [17].

Some emotions are universal, and all people experience them irrespective of their region or culture. In order develop a relationship between gestures and their corresponding emotions, various psychological models were investigated, and five were selected for being widely agreed upon [1]. These were: (1) Discrete emotional model (Paul Ekman's model) (2) Dimensional emotional model 2D (Russell's circumflex model of affect), (3) Dimensional emotional model 3D (PAD models), (4) 2D model (PANAS model), and (5) 3D model (Plutchik's model of emotions). Upon selecting the models, three of the most prominent emotions were identified namely, sadness, happiness, and excitement.

In this study, we have developed a novel method to recognize and predict emotions using flex sensors based wearable glove. First the hand gestures are recognized through the flex sensors attached on the glove. The gestures are translated into emotions based on the velocity and acceleration information of the hand motion. Three emotions (excited, happy and sad) are recognized based on four hand gestures (thumbs up, pointing finger, open fist and closed fist). Two different experiments are conducted on five healthy subjects to

Sara Ali, Aayesha Arif, Muhammad Baber Sial, Rumshaa Yunus, Yasar Ayaz, Rizwan Asif and M. Jawad Khan are with the National University of Sciences and Technology, Islamabad, Pakistan.
Noman Naseer is with Air University, Islamabad, Pakistan. (corresponding author, phone: +92-345-5296789; e-mail: jawad.khan@smme.nust.edu.pk).

International Journal of Mechanical, Industrial and Aerospace Sciences
ISSN: 2517-9950
Vol:12, No:9, 2018

compute the accuracy of the system. Overall, 77% accurate results are obtained. Our proposed design is suitable for both mute persons and children with autism spectrum disorder.

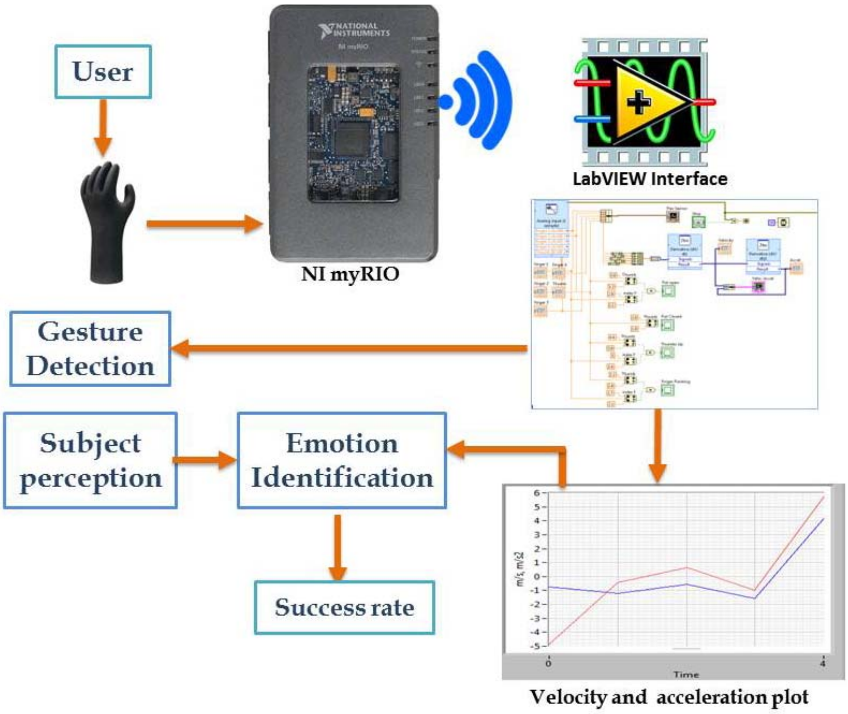

Fig. 1 System block diagram

II. Materials and Methods

A. System Architecture

In this study, our first step is to design a setup that can acquire muscle movement data from the user's hand and it can send the information about the detected gesture to a processing unit. The same can be done using image processing techniques, but in order to reduce the cost of the system we have only relied on flex sensors data [18]. The overall architecture of the system is shown in Fig. 1.

The two main components of the design shown in Fig. 2 are:

a) A glove with embedded flex sensors.
b) myRIO by National Instruments as processing unit.

The flex sensors mounted on the glove were positioned over the metacarpo-phalangeal (MCP) joints. The five sensors were connected in a series configuration supplied by a +5V pin from a myRIO forming a voltage divider network. The output of each sensor was fed to the myRIO via five analog input pins. Fig. 2 shows the connection diagram for the sensors and the respective myRIO inputs to which they were connected.

B. Hardware-Software Integration

A myRIO was connected to the target PC using Wi-Fi. The program was built on LabVIEW™ 2015. The data were read every 20 milliseconds or at the rate of 50 Hz. It was plotted in real time and a stop button was placed to stop the recording in the GUI. Fig. 3 shows the LabVIEW™ interface designed for gesture recognition.

Fig. 2 Gesture digitization glove assembly

All the five sensors were clustered together to calculate the parameters of velocity and acceleration to estimate the gestures. The data were plotted in real-time to identify the emotions. A look-up table was implemented that can classify the gestures on the basis of bending angle by measuring the voltage change at the individual sensors placed on the MCP joints. Four LEDs were placed on the GUI that light up corresponding to the gesture performed.

C. Choosing Gestures

Human anatomy and motion are quite complex. The communication through our body language varies widely in context of regions and cultures. However, there are a few gestures that have a universally accepted meaning. Keeping this in view, four gestures were chosen for this study: thumbs-up, pointing finger, open fist, and closed fist.

D. Subjects

We recruited five healthy subjects for the experiment. The average age of the subjects was 25± 2.5 years. All subjects gave a written consent prior to the start of the experiment. The experiment was conducted in accordance with the latest declaration of Helsinki.

E. Experiment

According to the literature, velocity and acceleration are reliable parameters for identification of emotions through gestures [11], [12]. An experiment was set up to verify the claims. A total of 17 volunteers were chosen to inspect the gestures performed by the subjects.

The volunteers were given a questionnaire based on the five chosen psychological models of emotions. Each of the four gestures was performed in front of the volunteers with varying the speed of hand movement in order to validate their relevance to a specific emotion. Every gesture was performed within a 10 second window. The high movement (H) speed corresponds to excited state, medium movement (M) represents Happy state, whereas slow (L) movement was indicator of sadness.

The inspectors guessed the emotion as per the performed action for each model. The results in Table I show the number of people that correctly perceived the emotion as was intended. For this part of the experiment, the performance speed was varied from low-to-high for two gestures of "thumbs-up" and "finger pointing". Table II shows the results for the gestures "closed fist" and "open fist" when the speed of the gestures was varied randomly.

TABLE I
PERCEIVED EMOTIONS WHEN GESTURE INTENSITY IS VARIED IN ASCENDING ORDER

Model	Expected Emotion	Gestures	
		Thumbs-up	Pointing Finger
		Correct Perceptions (out of 17)	
Model 1	Sad (L)	16	15
	Happy (M)	10	13
	Excited (H)	12	16
Model 2	Sad (L)	16	16
	Happy (M)	13	13
	Excited (H)	16	14
Model 3	Sad (L)	12	14
	Happy (M)	14	17
	Excited (H)	15	15
Model 4	Sad (L)	14	16
	Happy (M)	13	14
	Excited (H)	14	14
Model 5	Sad (L)	14	15
	Happy (M)	14	11
	Excited (H)	11	15

TABLE II
PERCEIVED EMOTIONS WHEN GESTURE INTENSITY IS VARIED RANDOMLY

Model	Intended Emotion	Gestures	
		Fist Closed	Fist Open
		Correct Perceptions (out of 17)	
Model 1	Sad (L)	11	14
	Happy (M)	9	14
	Excited (H)	16	16
Model 2	Sad (L)	12	12
	Happy (M)	9	12
	Excited (H)	15	14
Model 3	Sad (L)	9	12
	Happy (M)	14	11
	Excited (H)	16	12
Model 4	Sad (L)	13	12
	Happy (M)	11	12
	Excited (H)	13	14
Model 5	Sad (L)	10	10
	Happy (M)	10	11
	Excited (H)	13	11

III. RESULTS AND DISCUSSION

As the experiment was performed, the corresponding hand gestures were plotted along with their velocity and acceleration of performance. The results showed a positive relation between the chosen parameters and the anticipated emotions. Low velocity and acceleration values were recorded for gestures perceived as sad and the values increased for happy gestures and went even higher for excited gestures. Fig. 3 shows the data recorded for three different gestures for three different perceived emotions.

The performance of gestures was varied as inspectors identified the emotion they perceived. The accuracy of the identified emotions was found using the relation:

$$Accuracy = \frac{Correct\ Responses}{Total\ Responses} \times 100 \qquad (1)$$

For the case of sequential inputs, the average accuracy was 82%, whereas, for the random input our obtained results showed 72% accurate results. The accuracy decreased for the random case as the subject was unaware of the cue given. A verbal cue was given for this case and the subject hand movement speed was influenced due to the random stimuli therefore the performance was influenced.

The novelty of this work is that this is the first haptic device that is able to translate hand gesture into emotions. This device may be useful for the persons who cannot speak to communicate their emotions. Also, in case of autistic children, this device can further be enhanced to interpret the posture and gesture to express their emotions.

Another advantage of this work is that this is a low-cost device. Previous literature has used a camera to identify the human gestures [19]. In this case, a camera needs to be carried around in the real world to communicate a person's emotions, whereas, in our case a glove can be worn any time by a patient who needs to express his/her thoughts.

The current disadvantage of this work is that a bulky system is required to convert the gestures into emotions. Since the data are sent on a PC for conversion into emotions, the device may not be fully portable. However, this drawback can be improved with the used microcontrollers, etc.

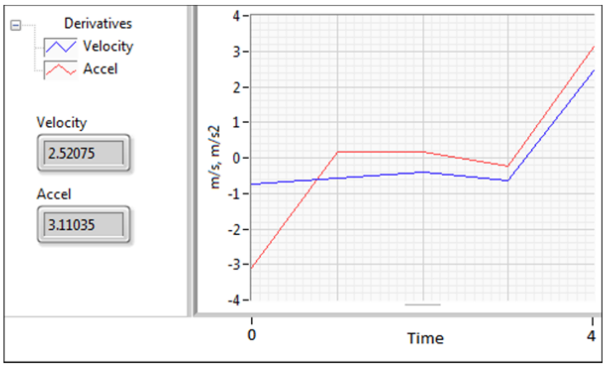

Fig. 3 (a) Velocity and acceleration plot for fist closed gesture when the perceived emotion is sad

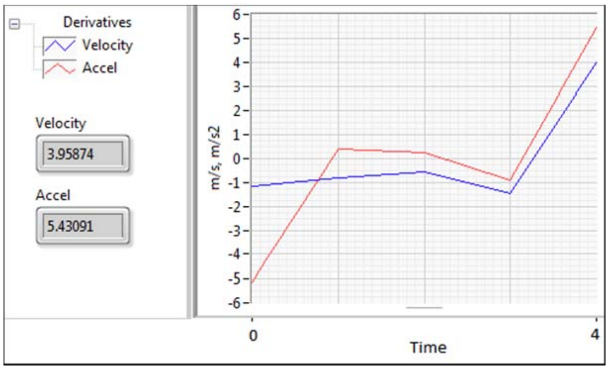

Fig. 3 (b) Velocity and acceleration plot for finger pointing gesture when the perceived emotion is happy

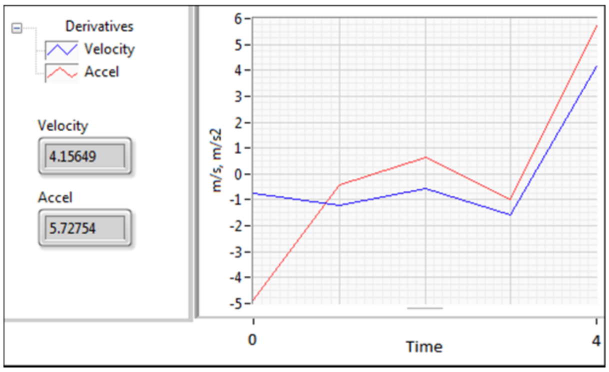

Fig. 3 (c) Velocity and acceleration plot for thumbs-up gesture when the perceived emotion is excited

Gesture recognition systems are now becoming important to human interaction with machines. There are various applications of such systems in assistive technologies [19]. As intelligent systems can further be enhanced, they need to be able to communicate with humans with natural ease. Thus, we need machines that are not only capable of reading human emotions but also of expressing emotions themselves. The wearable device presented here can find its applications in robot assisted therapy for children with autism spectrum disorder [20]. Creating a robot with an expressive face is certainly possible, but it incurs exorbitant costs [21]. The purpose here is to explore the possibility of a robotic system that does not require anthromorphic features to be able to communicate more naturally with humans. Further research on this issue can lead to better outcomes.

IV. Conclusion

In this study, a novel glove that can translate hand gestures into emotions was developed. The gesture was converted into emotions based on hand movement speeds. The gestures perceived as excited were measured using the highest for velocity and acceleration while happy gestures measure slightly lower. The gestures perceived as sad were found to have the lowest velocity and acceleration values. Four types of hand gestures were associated to three types of emotions. The experiment conducted on five subjects showed 77% accurate results.

Acknowledgment

This research was conducted under the umbrella of National University of Sciences and Technology, Islamabad, Pakistan.

References

[1] L. F. Barrett, “Discrete Emotions or Dimensions? The Role of Valence Focus and Arousal Focus,” *Cognition and Emotion*, vol. 12, no. 4, pp. 579–599, Jul. 1998.

[2] D. Cohen, G. Beattie, and H. Shovelton, “Nonverbal indicators of deception: How iconic gestures reveal thoughts that cannot be suppressed,” *Semiotica*, vol. 2010, no. 182, pp. 133–174, 2010.

[3] LF Barrett, M Lewis, JM Haviland Jones, *Handbook of Emotions*. New York: Guilford Press, 2016.

[4] P. A. Andersen, *Nonverbal communication: forms and functions*, 2nd ed. Long Grove, Ill: Waveland Press, Inc, 2008.

[5] S. Costa, F. Soares, and C. Santos, “Facial Expressions and Gestures to Convey Emotions with a Humanoid Robot,” in *Social Robotics*, 2013, pp. 542–55

[6] T. Hashimoto, S. Hitramatsu, T. Tsuji, and H. Kobayashi, “Development of the Face Robot SAYA for Rich Facial Expressions,” in *2006 SICE-ICASE International Joint Conference*, 2006, pp. 5423–5428.

[7] M. Kipp and J. C. Martin, “Gesture and emotion: Can basic gestural form features discriminate emotions?,” in *2009 3rd International Conference on Affective Computing and Intelligent Interaction and Workshops*, 2009, pp. 1–8.

[8] A. P. Atkinson, M. L. Tunstall, and W. H. Dittrich, “Evidence for distinct contributions of form and motion information to the recognition of emotions from body gestures,” *Cognition*, vol. 104, no. 1, pp. 59–72, Jul. 2007.

[9] R. M. Edith and A. B. Haripriya, “Gesture recognition using real time EMG,” in *2015 International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS)*, 2015, pp. 1–3.

[10] K. Dermitzakis, A. H. Arieta, and R. Pfeifer, “Gesture recognition in upper-limb prosthetics: A viability study using dynamic time warping and gyroscopes,” in *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2011, pp. 4530–4533.

[11] V. Kartsch, S. Benatti, M. Mancini, M. Magno, and L. Benini, “Smart Wearable Wristband for EMG based Gesture Recognition Powered by Solar Energy Harvester,” in *2018 IEEE International Symposium on Circuits and Systems (ISCAS)*, 2018, pp. 1–5.

[12] K. Kang and H. C. Shin, “EMG based gesture recognition using feature calibration,” in *2018 International Conference on Information Networking (ICOIN)*, 2018, pp. 825–827.

[13] A. Moin *et al.*, “An EMG Gesture Recognition System with Flexible High-Density Sensors and Brain-Inspired High-Dimensional Classifier,” in *2018 IEEE International Symposium on Circuits and Systems (ISCAS)*, 2018, pp. 1–5.

[14] T. K. Chan, Y. K. Yu, H. C. Kam, and K. H. Wong, “Robust hand gesture input using computer vision, inertial measurement unit (IMU)

and flex sensors," *Mechatronics*, vol. 2018, 2018.

[15] S. Shibata, K. Ohba, and N. Inooka, "Emotional evaluation of human arm motion models," in *Proceedings of 1993 2nd IEEE International Workshop on Robot and Human Communication*, 1993, pp. 346–351.

[16] C. L. Roether, L. Omlor, A. Christensen, and M. A. Giese, "Critical features for the perception of emotion from gait," *Journal of Vision*, vol. 9, no. 6, pp. 15–15, Jun. 2009.

[17] S. B. Sial, M. B. Sial, Y. Ayaz, S. I. A. Shah, and A. Zivanovic, "Interaction of robot with humans by communicating simulated emotional states through expressive movements," *Intel Serv Robotics*, vol. 9, no. 3, pp. 231–255, Jul. 2016.

[18] P. Kumari, L. Mathew, and P. Syal, "Increasing trend of wearables and multimodal interface for human activity monitoring: A review," *Biosensors and Bioelectronics*, vol. 90, pp. 298–307, Apr. 2017.

[19] J. P. Wachs, M. Kölsch, H. Stern, and Y. Edan, "Vision-based Hand-gesture Applications," *Commun. ACM*, vol. 54, no. 2, pp. 60–71, Feb. 2011.

[20] S. Tariq, S. Baber, A. Ashfaq, Y. Ayaz, M. Naveed, and S. Mohsin, "Interactive Therapy Approach Through Collaborative Physical Play Between a Socially Assistive Humanoid Robot and Children with Autism Spectrum Disorder," in *Social Robotics*, 2016, pp. 561–570.

[21] R. Aylett *et al.*, "Evaluating Robot Facial Expressions," in *Proceedings of the 19th ACM International Conference on Multimodal Interaction*, New York, NY, USA, 2017, pp. 516–517.