Vibrotactile feedback for conveying object shape information as perceived by artificial sensing of robotic arm

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Abstract This work is a preliminary study towards developing an alternative communication channel for conveying shape information to aid in recognition of items when tactile perception is hindered. Tactile data, acquired during object exploration by sensor fitted robot arm, are processed to recognize four basic geometric shapes. Patterns representing each shape, classified from tactile data, are generated using micro-controller-driven vibration motors which vibrotactually stimulate users to convey the particular shape information. These motors are attached on the subject's arm and their psychological (verbal) responses are recorded to assess the competence of the system to convey shape information to the user in form of vibrotactile stimulations. Object shapes are classified from tactile data with an average accuracy of 95.21 %. Three successive sessions of shape recognition from vibrotactile pattern depicted learning of the stimulus from subjects' psychological response which increased from 75 to 95 %. This observation substantiates the learning of vibrotactile stimulation in user over the sessions which in turn increase the system efficacy. The tactile sensing module and vibrotactile pattern generating module are integrated to complete the system whose operation is analysed in real-time. Thus, the work demonstrates a successful implementation of the complete schema of artificial tactile sensing system for object-shape recognition through vibrotactile stimulations.

Keywords Haptic perception · Object shape recognition · Vibrotactile feedback · Tactile data · Human computer interface

Introduction

Haptic perception is the sense of touch that independently allows one to distinguish the objects around him/her based on their characteristic properties like shape, size, deformability, texture, etc. For accurate fine tuning of manipulation of artificial arms they need to be amalgamated with haptic perception. Application spectrum of artificial hands includes rehabilitation, minimally invasive robotic surgeries, tele-navigation, virtual gaming environments and other areas of robotics and Human–Computer Interfacing (HCI) (Hayward et al. 2004). Moreover, several manufacturing plants require workers to wear thick gloves as a protective measure against highly corrosive chemical elements or high temperature, thereby hindering their tactile perception. Such application requires integration of artificial tactile sensing with human haptic perception. This work deals with object shape recognition from tactile data and conveying the object shape information to the human user in the form of vibrotactile stimulations. Local shape of various objects corresponds to basic geometric shapes and fusing such local information can provide a signature silhouette of the object under exploration and hence, aiding in its recognition. Researchers (Grunwald 2008) have shown that drawing patterns on subject's skin, i.e. passive touch, is capable of producing high recognition rates with high speed. The same principle is followed when object shape silhouettes are conveyed to the user in the form of vibrotactile stimulations.

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Artificial somato-sensory system (Eltaib and Hewit 2003) precisely has three integral parts: tactile sensor, tactile data processor (analyser) and tactile display. The sensor captures the raw data (time series of pressure values from sensor elements) which is generated on tactual contact with the object, the data processor extracts the required useful information from the raw data, and the tactile display (vibration of an array of motors shaped into a contour and attached to a subject) provides this information to the end user of the tactile system. Based on the field of application, the controller of a simulated character or a robotic hand fitted with tactile sensors may either be the end user himself/herself or a different individual. In either case, the tactile display provides the necessary feedback required for understanding the object property (here, shape) which is sensed at a remote environment, thereby creating a communication channel between artificial tactile sensation and human perception.

In HCI, the feedback signal to the human user is generally a physical quantity that can be sensed by human beings. Vibration, a distributed physical quantity, is considered in this work to substitute as the feedback signal due to the following reasons. In case of rehabilitation, the subject using a prosthetic device may have visual and/or auditory impairment due to which displaying the shape of the object or prompting the name of the object will not fulfil the purpose. In other application areas, where the subject is engaged in multi-tasking, vibration on human skin without engaging other sensory channels provides good alternative as other sensory channels might be vital for the task at hand. Also in tele-navigation, when the user is exploring surfaces/objects with robot arm, can perceive the somatosensation through vibrotactile feedback.

Ibrayev and Jia (2004) have derived differential invariants of low-degree polynomial curves which are considered to localize the object shape relative to the hand. Pezzementi et al. (2011) has formed mosaic of tactile images and used state estimation techniques for mapping, identifying and localizing raised alphabets. Pezzementi et al. (2011) has demonstrated haptic exploration of an object as a search problem in continuous space to explore and construct its appearance. This shows that research on object shape recognition has been in focus in various fields since its inception till date. On the other hand, vibrotactile pattern generation has recently gained attention which will assist in providing the necessary feedback for shape perception. Kohli et al. (2006) has explored vibrotactile apparent motion realised using three rings of five voice-coil tractors fitted to the upper arm of the subjects. Cincotti et al. (2007) has provided a survey of vibrotactile feedback for EEG-based Brain Computer Interfacing applications. Sarakoglou et al. (2012) has shown improvement in performing tele-

operation in presence of tactile and force feedback. King et al. (2009) has shown that without feedback of tactile information robotic manipulation are performed with greater forces than the optimum requirement for grasping objects. Weber et al. (2011) has compared vibrotactile and verbal commands for spatial guidance of objects. In multi-tasking environment, the work by Jonghyun et al. (2010) demonstrates communication using vibrotactile messages while performing driving-like task with higher priority. Similarly, Ying and Morrell (2013) has shown haptic feedback as a viable alternative for posture guidance without overloading visual sensory channel which is engaged in typing activity. Schwalk et al. (2015) have utilized vibrotactile motors attached to driver's seat and have shown that vibrotactile cues can efficiently serve as feedback channel for drivers especially in automated driving scenarios. Hasson and Manczurowsky (2015) have analysed velocity and position based vibrotactile feedback for enhancing the prosthetic arm control efficacy. Researchers (Shull and Damian 2015) have shown that tactile feedbacks can be utilized for various purposes, viz. sensory augmentation for those patients who are suffering from complete/partial sensory loss, and as sensory trainer where there is no sensory impairments. It is depicted that vibrotactile feedback can improve the controllability in applications like prosthetics and rehabilitation and can be employed as comfortable wearable. Wang et al. (2016) have also rationalized the usage of vibrotactile stimulations as wearable devices for information communication transmission. Without interfering with other sensory channels, due to the minimal commotion and maximal effect in invoking attention, vibrotactile feedback mechanisms are effective and practical. Kurihara et al. (2014) have developed a virtual reality system where the subjects feels like a robot. They have developed mechanism in an immersive environment where the vibration and other kinematic information are obtained from a robot and are employed as feedback through visual, audio as well as haptic channels. It is established that tactile feedback is essential along with audio and visual counterparts in invoking the required sensations in the subjects. Li et al. (2015) have tested various parameters, viz. frequency, duration and amplitude, of vibrotactile stimulation for analyzing the contribution of these parameters in efficacy of a navigation system through vibrotactile feedback. They (Li et al. 2015) have inferred that though mid-level amplitude and duration is most effective, however, the optimal level of these parameters are subject dependent. Walker et al. (2015) have demonstrated that vibrotactile feedback is extremely crucial in providing the object slip information of a prosthetic arm. This slip information in the form of vibrotactile feedback, along with the force feedback i.e.

object contact information enable enhanced controllability manipulation of the artificial arm by the user. Moreover, the vibrotactile feedback does not engage the visual channel, thus is expedient for multitasking real life environments. These work not only shows that haptic display is an essential component for bio-inspired artificial limb but also indicates the potential of tactile feedback as a parallel sensory channel to audio/visual senses. However, artificial tactile sensing followed by vibrotactile feedback in a single framework and that too for transmitting object shape information has not been developed of late as to the best of author's knowledge.

This work aims at constructing an artificial tactile system capable of recognizing generic object shapes as a preliminary work to endow human-like haptic perception to artificial hands and their user. The work is divided in three modules. The first module addresses machine learning algorithms for recognition of four generic object shapes from tactile data acquired from exploration of different objects by sensor fitted robot hand. The second module involves in developing vibrotactile stimuli for tracing out the contour of the four types object shapes. The third module assesses the understanding of the vibrotactile signals conveying object shapes by analysing the verbal/psychological response of different subjects to whom the stimuli is applied. The vibrotactile stimuli are applied to the same subjects over three successive days to explore the possibility and extent of learning. In the first module, the tactile data are processed to obtain adaptive auto-regressive (AAR) parameters as features which are classified by Naïve Bayes (NB) classifier. In the second module, the vibrotactile stimuli is realised by generating square wave pattern which actuates eight coin vibration motors to express the object shape to the subject. The three modules are independently developed and analysed. Following this, the modules are integrated to complete the system and its performance is analysed in real-time.

Rest of the paper is organized as follows. The “[Materials and methods](#)” section briefly describes the different steps of the experiment. The “[Results and discussion](#)” section declares and presents the different performance indices to analyse and validate the proposed algorithm. Finally, the “[Conclusion](#)” section summarizes the work and concludes the paper.

Materials and methods

This study identifies object shapes from tactile data, uses vibration motors interfaced with a general purpose micro-controller to produce vibrotactile feedback to the subject and analyses the subjects' verbal response for shape perception. The classifier, implemented to recognize object shape from

tactile data, is trained offline and used in the real-time for the complete integrated system. Thus, it creates an interface between artificial tactile sensation of robot arm and vibrotactile perception of human for object shape recognition. The flowchart depicting the course of the work and experimental setup are shown in Fig. 1a, b respectively.

Materials

This study addresses four basic and most commonly found geometric shapes viz. sphere, cuboid, cylinder and cone. Four rigid objects, approximately matching each shape, including a wooden prototype for each kind is considered for tactual sensing using a robotic arm. The objects dimensions are chosen such that the objects can be easily grasped by the robot gripper. Different objects of different shapes considered in this work are summarized in Table 1.

Subjects

The schematic of the study involves controlling the tactile sensor fitted JACO robotic arm (Maheu et al. 2011) by a subject to explore an object kept in front of it and applying the vibrotactile feedback of the recognized object shape to another subject who is blind-folded and ear-plugged. JACO arm is controlled by 10 healthy operators (6 female and 4 male) in the age-group of 25 ± 3 years. The vibrotactile feedback is given to 10 healthy subjects (other than the operators) (5 female and 5 male) in the same age group who are not informed about the vibrotactile patterns corresponding to the different shapes of the considered objects prior to the experimentation. Real-time system is tested with these 10 pairs of subjects who have earlier participated in the data acquisition, i.e. 10 subjects operate JACO and 10 subjects analyse the vibrotactile feedback. All the 20 subjects were asked to sign a consent form for participation. The institutional committee was informed in details about the experimental objective and procedure, which they had agreed upon. Thus all the ethical issues are considered relating to human subject experiments. All the procedures are non-invasive and all safety norms are abided, assuring protection of the subjects. Helsinki Declaration of 1975, as revised in 2000 (Carlson et al. 2004), is followed for dealing with human subjects for experimental purpose.

Object shape classification from tactile data

JACO arm is controlled by several subjects for exploring the given objects to understand the shape of the objects by sequential processing of its contour. Auto-regressive parameters are extracted from the acquired data following

Fig. 1 Steps of the work: **a** schematic diagram; **b** experimental setup

which Naïve Bayesian classifier is trained to recognize object shapes.

Tactile data acquisition

Tactile data is acquired using JACO arm (a product of Kinova Robotics) fitted with Tekscan tactile sensor and controlled by different subjects. Tekscan Grip system for R

& D (<http://www.tekscan.com/grip-pressure-measurement>) is used for acquiring data corresponding to pressure distribution during palpation. Grip Research 6.70 is the associated software that converts the voltage output of the resistive sensor elements to pressure values in pounds per square inch (psi). The sensor consists of 18 segments to be attached to fingers and different regions of palm. The gripper of JACO arm has three fingers. The sensor segments corresponding to thumb, ring finger and little finger are loosely attached to the fingers of JACO such that no pressure is sensed when the fingers are flexed and extended in air. The pressure sensor and its attachment to JACO arm is shown in Fig. 2.

The minimum sensor resolution in terms of number of time series is selected so that lesser data processing is needed and hence, lesser time and space complexity in real-time environment is offered. At the lowest interpolation, considering all the nine segments labelled in Fig. 2a, a total of 153 time-series are produced. The sampling rate for tactile data acquisition is set at 10 frames per second.

A stimulus consisting of successive commands of ready (for 2 s), explore (for 10 s) and wait (for 3 s) is shown to the subject. During ready phase (2 s duration) of the stimulus, the item to be explored is placed in front of the JACO arm by the experiment session-in-charge. The subject dynamically explores the object by controlling the JACO arm during the explore phase (10 s duration). To accomplish the exploration procedure, a robot operator controller grasps and releases the object every 2 s in this phase in between which the experiment session-in-charge randomly rotates the object in a different dimension. Each of the 16 objects mentioned in Table 1 is explored 5 times by each subject. This provides a data set of $16 \text{ (objects)} \times 5 \text{ (number of times each object is explored)} = 80$ observations for each of the 10 subjects.

Tactile data pre-processing and feature extraction

The data acquired from the tactile sensor for each observation is arranged in the form of a matrix of dimension $100 \text{ sample points (sampling rate} \times \text{duration)} \times 153 \text{ time-series}$. Adaptive auto-regressive (AAR) (Nai-Jen and Palaniappan 2005; Schlögl 2000) parameters are extracted from each of these time-series which are then horizontally concatenated to form a feature vector.

Experimentally it is found that for lower order AAR models, the accuracy of estimation is less and for order higher than 6, the accuracy does not improve. During the training phase of supervised learning, the process of training using random parameters using the training dataset followed by testing using a small dataset, disjoint from both the training and the dataset, is known as validation and this process is widely used for choosing the training

Table 1 Different objects considered for recognition based on object shapes

Shapes	Dimensions	Objects
Sphere	Radius: 2.5 ± 0.5 cm	Wooden prototype, plastic ball, orange, spinning top
Cuboid	Length: 13.5 ± 4.0 cm Breadth: 5.0 ± 2.0 cm Height: 2.5 ± 1.0 cm	Wooden prototype, laptop adapter, pencil box, smartphone
Cylinder	Radius: 2.5 ± 0.5 cm Height: 6.5 ± 1.5 cm	Wooden prototype, candle, beaker, metallic pipe
Cone	Base radius: 3.0 ± 0.5 cm Height: 7.0 ± 1.5 cm	Wooden prototype, funnel, tapered pet bottle, ice-cream cone

Fig. 2 Robot arm and pressure sensor: **a** Tekscan pressure sensor: segments 1–9 (corresponds to thumb, ring finger and little finger of human palm); **b** attachment of the nine sensor segments to JACO robot arm

parameters in order to avoid over-fitting of data so that the generalization is good. Thus, AAR model of order 6 has been used for feature extraction. The rate at which the time-varying parameters of the AAR model changes is called update coefficient which is heuristically chosen as 0.0085 thereby allowing slow changes in the parameters.

From each of the time-series 6 AAR coefficients are obtained by averaging all the 6 AAR parameters obtained at different instants. Thus from 153 time-series, a 918-dimensional feature vector of is obtained.

Classification

The feature set obtained from the tactile data is fivefold cross-validated and classified using Naïve Bayesian (NB) classifier (Lepora et al. 2011; Machado et al. 2013; Érdi 2015). Bayes theorem calculates the posterior probability of a class (object shape) given the feature vector of the unknown sample and classifies the unknown sample to that class which yields the highest probability.

In this work the probability density function (pdf) of every feature within a class is modelled using Gaussian distribution whose mean and standard deviation are learned during the process of training. The prior probability of every class is estimated from the relative frequencies of samples of every class. This work uses a one-against-all

framework followed by majority voting to decide the class of the object.

Vibrotactile pattern recognition

After identifying the object shape from tactile data, it is feedback to the subject for his/her vibrotactile perception. For generating a vibrotactile signal, eight brushless DC motors are actuated using square wave generated with the help of AtMega16, a general purpose microcontroller unit (MCU), which is interfaced with the motors using a driver circuit. When the motors are attached in a cylindrical manner as shown in Fig. 1a to any cylindrical part like hand or leg of the subject, the motors are actuated in a pattern tracing out the contour of the object. This provides the vibrotactile display to the subject to convey the object shape information.

Vibration motor

The vibratory action is realised with the help of eight coin brushless DC motors (Fig. 3). These motors have unbalanced loads in their rotors which causes the motors to vibrate during rotation upon electrical excitation (Niwa et al. 2004). The output frequency of vibration (200 Hz) of these motors is fixed, however the output intensity of vibration varies proportionately with the input voltage. The appearance and specifications of these vibration motors are given in Fig. 3.

Control signal generation

Each of the vibration motors is triggered by a control signal specific to that motor. The motors are excited in a manner such that a smooth apparent motion is felt by the subject on his/her skin. This is accomplished by switching overlapped square wave for different motors in specific patterns generated using AtMega16, an 8-bit processor (<http://www.atmel.in/Images/doc2466.pdf>) operating at 8 MHz. Two parameters viz. T_{ON} (duration of a square pulse) and T_D (delay between the successive square pulses) and the

Fig. 3 Coin brushless DC motor and its specifications

placement of the motors control the smooth apparent motion generating the contours of the objects and thus, expressing the object shapes to the subject (Sherrick 1968). From literature (Niwa et al. 2009), 800 ms and 400 ms are found to be appropriate for T_{ON} and T_D respectively for rendering the vibrotactile stimuli to be easily understood by the subject. In this work, using $T_{ON} = 600$ ms and $T_D = 450$ ms provides better responses from the subjects in the minimum possible time. Thus, the duty cycle, the percentage overlap of the square waves and the specific pattern for triggering the motors are fed to the MCU prior to experimentation. The object shape classification output from tactile data, performed in MATLAB R2012b environment, is provided as input to the MCU via a serial port and the corresponding vibrotactile pattern is generated via embedded programming.

The generation of square wave pattern for a sphere is represented in Fig. 4 along with the various specifications of the waveform.

Interfacing the motors directly at the MCU output fails to drive the motor due to the lack of sufficient power. Hence, the output of the MCU is power amplified by an array of eight similar transistor based driver circuit each driving one of the motors. This driver circuit is an emitter follower as shown in Fig. 5. Each driver circuit is powered from a 3.5 V voltage regulator and provides an output in the range 3–3.2 V and 30–78 mA which meets the electrical specifications of the motors.

Vibration pattern actuation

For each of the four shapes, four triggering patterns of motors takes place in the manner discussed in the “Control signal generation” section. The actual sequence of triggering is mentioned in Table 2 where $m_i - m_j$ ($i, j = 0-7$) denotes triggering of motor m_j follows triggering of motor m_i and m_i/m_j ($i, j = 0-7$) denotes triggering of motors m_i and m_j occurs simultaneously.

As the duration of each square wave (one epoch) is d seconds, four actuation of a motor (one cycle) takes approximately $4 \times d$ seconds. After the completion of one cycle, a finite delay is provided and the sequence is repeated again. This delay is chosen to be 500 ms. The number of times a cycle is repeated to convey a shape depends on the sensory understanding by the subjects. After a few trials, most of the subjects have successfully recognized the patterns in two cycles. Thus, the duration of one vibrotactile display takes roughly 20 s as two cycles each for 9600 ms as shown in Fig. 4 is executed with 500 ms of delay in between the cycles.

Psychological response analysis for vibrotactile feedback assessment

For validating the vibrotactile feedback, the object shape as understood by the subject is analysed from the verbal response as prompted by the subjects. Prior to the experiment, the subjects were informed about the broad category of the four shapes (i.e. cuboid, sphere, cylinder and cone) and were asked to report the shapes to which they could map the pattern whose contour is being vibrotactually traced. However, as simply the contour of the objects were traced rather than some encoded motor sequence representing the shape, it was easy for the subjects to correlate the shape and the motor sequence. The main idea of the experiment is to make the subject feel the contour of the three dimensional shapes only through the vibrotactile stimulations, without seeing or even touching the concerned object. For this purpose, blind-folded and ear-plugged subjects are stimulated with a specific vibration pattern for 20 s after which a feedback interval of 3 s is provided during which vibrotactile signal is not given to subject. In the feedback interval, the subject prompts the name of the object shape as is felt by them and then relaxes. The procedure is repeated 20 times for each of the four object shapes in a random fashion which assures unbiased responses. Hence, there are $20 \times 4 = 80$ observations for each subject. This vibrotactile feedback assessment is repeated for 3 consecutive days for each of the 10 subjects.

Operating the integrated system in real-time

After all the classifiers are trained offline, the complete integrated system as represented in Fig. 1b is tested in real-time scenario. At first, all the subjects are asked to relax for 20 s. Following this, the experiment session in-charge places the object to be explored in front of the sensor fitted JACO arm in the ready phase of 2 s. The subject to operate the JACO arm becomes alert in the ready phase and explores the object provided to JACO in the explore phase

Fig. 4 Timing diagram for motor actuation along with various specifications, where motors are actuated in the sequence to generate the sensation of the shape: sphere

of 10 s. A similar exploration procedure is followed as was done during the offline phase. The tactile data is processed and object shape is recognised using the pre-trained NB classifier in the following 3 s of wait phase during which

Fig. 5 Driver circuit interfacing an MCU output and a DC motor

the JACO operator relaxes. Following this, the vibration motors are actuated to generate a specific pattern for 20 s depending on the output of the classifier. After the vibration stops, the subject verbally gives the feedback of the object shape as sensed by him/her in the next 3 s. The total process starting from alignment of JACO arm to the feedback of the shape perception is repeated for each of the 10 pairs of subjects where objects of different shapes are randomly explored to obtain 40 trials. For each trial, if the shape is misclassified by the pre-trained NB classifier or the shape is misinterpreted by the blind-folded ear-plugged subject both leading to erroneous verbal response from the subject, the same object is again presented to the subject for exploration until correctly guessed by the subject.

The visual cue shown to the subject for tactile data acquisition is shown in Fig. 6a, the cue used by the session in-charge of vibrotactile feedback assessment is shown in Fig. 6b and the cue used in the synchronous online integrated system is shown in Fig. 6c.

Table 2 Sequence of actuation of vibration motors for different object shapes

Shape	Sphere	Cuboid	Cylinder	Cone
Sequence of actuation	$m_0-m_1-m_2-m_3$ 	$m_0-m_3-m_7-m_4$ 	$m_0/m_4-m_1/m_5-m_2/m_6-m_3/m_7$ 	$m_4-m_5-m_0-m_7$

Results and discussion

The performance NB classifier in training phase is evaluated on the basis of four parameters which are classification accuracy (CA), sensitivity (sens), specificity (spec) and processing time of the raw data (pre-processing time + feature extraction time + classification time of a single observation). As a performance index of the real-time system, information transfer rate and utility of the integrated system are noted. The study is performed in MATLAB R2012b executed on a computer having Intel Core i3 @ 2.30 GHz processor and 4 GB RAM.

Object shape classification from tactile data

The tactile dataset is fivefold cross-validated to obtain 60 % of the dataset as the train-set, 20 % as the validation-set and the rest as the test-set. The classifier is trained using the train-set in each fold, the selection of feature and classifier parameters is checked to clear the possibility of over-fitting using the validation-set and the performance

Table 3 Result of classification of tactile data

Classes	CA (%)	Sens (%)	Spec (%)
Sphere	97.50 ± 1.65	100.00 ± 0.00	95.00 ± 0.31
Cuboid	96.67 ± 1.38	98.33 ± 0.27	95.00 ± 1.23
Cylinder	91.67 ± 0.91	90.00 ± 0.92	93.33 ± 0.85
Cone	95.00 ± 1.42	95.00 ± 0.47	95.00 ± 0.62
Mean	95.21 ± 2.60	95.83 ± 4.02	94.58 ± 1.05
Time (s)	2.6166		

parameters are obtained using the test-set. The performance indices are averaged over 10 subjects and noted in Table 3.

From the results in Table 3, it is noted that the classifier distinguishes all the four shapes accurately with an average accuracy of 95.21 % and standard deviation of 2.60 i.e. the classifier is not biased for the recognition of any particular shape. Results also show high specificity and high sensitivity of the different classes. Moreover, the average processing time of an observation is seen to be <3 s which validates the choice of considering 3 s as the wait phase in real-time testing scenario.

Fig. 6 Visual stimulus for different experiment: **a** for tactile data acquisition, **b** for data acquisition for psychological analysis of vibrotactile feedback, **c** for real-time implementation of the integrated system

Table 4 Result of psychological analysis (recognition rate) of vibrotactually generated feedback

Day	Recognition rate (%)
1	75.00 ± 5.75
2	87.50 ± 4.25
3	95.00 ± 2.50

Object shape classification from vibrotactually stimulated verbal response

Table 4 mentions the average recognition rate and standard deviation over 10 subjects from psychological analysis (verbal response) of the vibrotactile feedback carried out from the verbal response given by each subject. The recognition rate is calculated as the percentage of correct prediction made by the subject on application of the 80 (20 times for 4 objects) vibrotactile stimulus on the subject's hand on a single session.

From Table 4 it is observed that the psychological recognition rate (75 % to 95 %) improves from day 1 to day 3 which indicates learning is taking place through feedback presentation in form of vibrotactile stimulations.

Performance analysis

The results obtained in the online phase are measured by the information transfer rate (ITR) and utility metrics. To validate the results obtained during offline training phase, the overall accuracy is compared with the performance of the other standard classifiers using Friedman's Test.

Information transfer rate

Information transfer rate (Obermaier et al. 2001; Yuan et al. 2013) is the bit-rate of the system measured in bits/symbols as given by Eq. (1) where N is the number of choices which is 4 for the four different shapes and P is the normalized accuracy for classifying tactile data using NB classifier trained offline. However, measuring bit-rate in bits/min is more significant. Hence, Eq. (1) is modified to Eq. (2) where T is the average time (in second) per trial. Including the interval for tactile data acquisition along with

the processing time for each observation, the average time per trial T turns out to be 12.3613 s. Thus, ITR gives the real-time classifier performance. ITR for all the 10 pairs of subjects are noted in Table 5.

$$B = \log_2 N + P \log_2 P + (1 - P) \log_2 [(1 - P)/(N - 1)] \quad (1)$$

$$B_t = B \times 60/T \quad (2)$$

In Table 5, it is observed that the bits/shape (B) over all the pairs of subject has a standard deviation of 0.1312, with minimum and maximum ITR of 1.3883 and 1.7917 respectively, which indicates that the proposed system is able to classify the 4 classes of shapes for all the subjects. It is also observed that the ITR value (B) is highest for subject pair P3 indicating that among the 10 subjects the best learning of vibrotactile pattern has taken place for that particular subject.

Utility of the integrated system

As the considered tactile sensing part interfaced with the vibrotactile pattern generation part as the complete system, measuring the classifier performance using ITR alone does not sufficiently analyse the complete system quantitatively. Thus, to measure the performance of the classifier part along with the control signal generating part the utility metric (Dal Seno et al. 2010) is used. It is the ratio of the expected average benefit to the average time needed to achieve it. Average benefit (b_L) is the average information conveyed. Thus, considering N choices and equal probability of all choices, $b_L = \log_2 N$ bits is obtained. Average time (T_L) to get the benefit is recursively defined by Eq. (3) in terms of the fraction of correct guesses (p) by the subject who is vibrotactually stimulated, and duration (c) to convey a single shape correctly [indicated by the first term in Eq. (3)] or incorrectly [indicated by the second term in Eq. (3)]. In the latter case the object is again explored until its shape is correctly conveyed. This duration to convey a single shape correctly is labelled in Fig. 6c where the interval from starting exploration of an object to the time when the vibrotactile feedback signal ends chalking out its

Table 5 Information transfer rate and utility of real-time experiment

Pair ID	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
P	0.9167	0.9667	0.9750	0.9033	0.9250	0.9306	0.9578	0.9374	0.9608	0.9435
B (bits/shape)	1.4543	1.7365	1.7917	1.3883	1.4968	1.5263	1.6808	1.5631	1.6993	1.5971
B_t (bits/min)	7.0588	8.4289	8.6967	6.7385	7.2653	7.4086	8.1585	7.5871	8.2480	7.7519
p	0.7750	0.9000	0.9250	0.7250	0.8750	0.8750	0.8750	0.8250	0.8000	0.8250
U (bits/min)	2.7547	3.2591	3.3623	2.5581	3.1567	3.1567	3.1567	2.9542	2.8541	2.9542

pattern. However, the classification time during the wait phase varies. In order to make the metric more significant the average classification time is considered instead of the wait phase of 3 s to measure c . Thus, the value of c turns out to be 32.618 s (or 0.544 min). When the object shape is incorrectly guessed by the subject, before further exploration of the same object a delay (b) occurs due to the intervals for verbal feedback from the subject (3 s) and the ready phase of the next stimulus (2 s). Thus, b turns out to be 5 s (or 0.083 min).

$$T_L = pc + (1 - p)(c + b + T_L) = c + (1 - p)(b + T_L) \quad (3)$$

By substituting T_L continuously in Eq. (3), a sum of a geometric progression is obtained as shown in Eq. (4). The series in Eq. (4) converges to Eq. (5) if $p > 0$.

$$\begin{aligned} T_L &= c + (1 - p)(b + T_L) \\ &= c + (1 - p)(b + c + (1 - p)(b + T_L)) \\ &= c + (1 - p)(b + c) + (1 - p)^2(b + T_L) \\ &= b + c + (1 - p)(b + c) + (1 - p)^2(b + c) \\ &\quad + (1 - p)^3(b + c) + \dots - b \\ &= (b + c) \sum_{i=0}^{\infty} (1 - p)^i - b \end{aligned} \quad (4)$$

$$\begin{aligned} T_L &= (b + c)/p - b \quad \text{if } (1 - p) < 1 \\ &= (b + c - bp)/p \\ &= \{(1 - p)b + c\}/p \end{aligned} \quad (5)$$

Thus, utility (U) in bits/unit time, is given by Eq. (6) and its values over the 10 pairs of subjects are stated in Table 5. As noted in case of ITR, the standard deviation of U is 0.2472 over all the subject pairs which is very small and hence, it indicates that the system successfully transmits shape information from the artificial sensing system to the human user through vibration motors for all cases.

$$U = b_L/T_L = (p \log_2 N)/\{(1 - p)b + c\}. \quad (6)$$

Statistical test

The result of classification of tactile data using NB classifier is validated by Friedman Test (Demsar 2006) against four other standard classifiers viz. Linear Support Vector Machine (LSVM), Support Vector Machine with Radial Basis Function as kernel (RBF-SVM), k -Nearest Neighbour (k NN) classifier and Linear Discriminant Analysis (LDA).

Using the validated parameters, the average ranks of the classifiers R_j based on the classification accuracy are mentioned in Table 6.

According to the null-hypothesis, all the classifiers are equivalent and hence, they should provide the same result. The Friedman statistics with $(k-1)$ degrees of freedom is given by Eq. (7) where k is the number of classifiers (5 in this case), N is the number of datasets and R_j are the ranks of the classifiers averaged over all the subjects as mentioned in Table 6.

$$\chi_F^2 = [12N/\{k(k+1)\}] \times \left[\sum_{j=1}^5 R_j^2 - \{k(k+1)^2\}/4 \right] \quad (7)$$

As the feature-set is prepared by considering the tactile data from all the 10 subjects, thus, $N = 10$ datasets. Using the above parameters, the Chi square value from tactile data-set is obtained as 26.56 which are greater than $\chi_{4,0.05}^2 = 9.49$, the critical value of Chi square for 4 degrees of freedom at 95 % confidence interval. Thus, 95 % confidently it can be asserted that the null hypothesis is wrong and the classifiers are not equivalent but ranked according to the ranks given in Table 6. This validates the choice of NB classifier and the results obtained using the proposed feature-classifier pair.

Comparison with other works

Ibrayev and Jia (2004) have derived differential invariants of low-degree polynomial curves which are fitted to two points on the boundary of the object to derive the local geometry. The actual curve is determined in its parametric form and then the contact points are considered to localize the shape relative to the hand. However, most of their work is based on simulation results and has not been applied to practical cases for field testing. Pezzementi et al. (2011) has considered object shape reconstruction and recognition as a search problem in continuous space. Simulation based experiment is done to identify complex shapes using bag-of-features framework, following which the framework is tested to identify raised alphabets thereby validating their proposed work but only in a limited environment in practical scenario. Cincotti et al. (2007) has used vibrotactile channel for a flow of feedback signals to the subjects participating in EEG-based motor imagery experiments. The study also revealed the vibrotactile modality has reliability comparable to classical visual feedback and its advantages surface when the visual channel is engaged in some other task like cursor movement (as experimented). Although the work shows that the vibrotactile channel is informative yet its capability is explored very little conveying only the sense of direction. Kohli et al. (2006) has explored vibrotactile apparent motion which is studied

Table 6 Average classification accuracies and Ranks of classifiers for Friedman statistics

Classifiers	LSVM	RBF-SVM	KNN	LDA	NB
Parameters	$C = 100^a$	$C = 100, \sigma = 10^b$	$k = 3$, City-block distance	Gaussian distribution	Gaussian distribution
Classification accuracies (%)	89.18	84.93	91.87	85.50	95.21
Rj for tactile dataset	2.9000	4.3500	2.3500	4.1500	1.2500

^a C = Smoothing parameter for SVM^b σ = Standard deviation of the Gaussian kernel for RBF-SVM

using different speed (fast, medium or slow) and pattern (up, down, clockwise and/or counter-clockwise). Successful pattern identification is concluded. This pattern could be used convey encoded information but such a system is not built into. Though Walker et al. (2015) have utilised vibrotactile feedback to reduce object slip information, but they have not integrated with tactile sensor information as well as the work does not provide object shape information to the user. Researchers (Niwa et al. 2004, 2009; Obermaier et al. 2001; Dal Seno et al. 2010; <http://www.atmel.in/Images/doc2466.pdf>) have analysed efficacy of vibrotactile stimulation, various parameters to improve its efficacy and have implemented them in providing information about navigation mostly. Thus, this present work for the first time assimilates the object shape recognition by an artificial sensing system and this shape information is also transmitted to human over the vibrotactile channel for his/her shape perception. The work is also tested in real-time scenario which validates its applicability even further than the offline results from independent tactile sensing and vibrotactile feedback modules.

Conclusion

This work addresses a preliminary approach to design a communication channel between a tactile sensor fitted artificial hand and shape perception of human bypassing the innate neuro-muscular pathway of human beings for the above purpose. The sensor fitted JACO arm is used to explore an object over 10 s interval during which tactile data are acquired. AAR parameters extracted from the data are classified by NB classifier to distinguish four basic geometric shapes of objects. Classification accuracy of 95.21 % is obtained in a processing time of 2.6166 s. Following this, square wave patterns are generated using AtMega16 which are fed to eight coin DC motors via a driver circuit, which are attached to the right forearm of the subject. On actuation of the motors, a unique pattern for every shape is generated and blind-folded, ear plugged subjects are asked to recognize these patterns representing common 3D object shapes. From their verbal response representing psychological analysis, their understanding of

object shape from vibrotactile stimuli is studied. Repeated application of stimuli, over three sessions, shows an improvement in recognition rate from 75 to 95 % for psychological analysis. This indicates occurrence of learning of the stimuli. The complete framework developed piece-wise in offline environment is integrated and analysed in real-time. Thus, this work presents an alternative channel (vibrotactile feedback modality) for conveying tactile information sensed at a remote environment to human without interfering with the standard visual/auditory channel which may either be disabled in handicapped person or may be engaged in some other work for a healthy person.

With the successful development and implementation of the proposed system, we look forward to extend the work where distinguishing complex shape as a combination of basic shapes will be possible. Moreover, other properties of objects need to be recognized and implemented in a similar manner which can aid in all-round recognition of every single object.

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