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Response Times of a Tactile Motion Intent Recognition System

T. Stefanou[1], G. Chance[2], T. Assaf[2], S. Dogramadzi[2]

[1]*Bristol Robotics Laboratory, University of Bristol, UWE*

[2]*Bristol Robotics Laboratory, UWE*

thekla.stefanou@bristol.ac.uk

INTRODUCTION

In the quest for high performance and consistency in motion intent recognition systems we experiment with tactile sensing. We investigate the potential of a tactile motion intent recognition system for use in autonomous rehabilitative and assistive devices. The focus of this work is on the latency of its motion detection.

Looking at upper limb motion intent recognition we aim to capture and interpret the tactile cues that arise. We used a tactile arm brace, the TAB, placed on the forearm to detect muscle activity while performing gripping motions using a bespoke 3D printed and sensorised gripping device. Analysis of the data showed that the TAB detects gripping instances, on average, 0.26s before gripping device.

METHODOLOGY

Tactile Sensing

The muscle contraction that takes place during gripping can be captured on the skin surface using tactile sensing. Our aim to mimic the recognition of movement intent as done in a therapist-patient setting; the therapist lightly touches the arm to sense the contraction of the muscles before guiding the limb through the exercise.

Prior studies have shown that weak forearm muscle contractions can be detected using inexpensive force sensors (Stefanou et al. 2017). The potential of force myography, or tactile imaging, is still being explored to determine whether it can be an alternative to the conventional electromyography techniques (Ravindra&Castellini 2014). For the purposes of these studies, the TAB and a gripping device have been designed and built.

The TAB

The TAB is made up of 8 force sensitive resistive (FSR) sensors uniformly distributed around a flexible, adjustable arm band. In all the user experiments performed, the TAB was placed on the right forearm and the gripping device was held as shown in Figure 1. The gripping device uses two button load cells to measure the force experienced as two rods, attached to the handle of the device, press vertically against each one. During gripping, the strength being was proportional to the individual FSR sensor readings, Figure 2. The data used in this study included experiments that incorporated power, precision, tripod and pinch gripping motions.

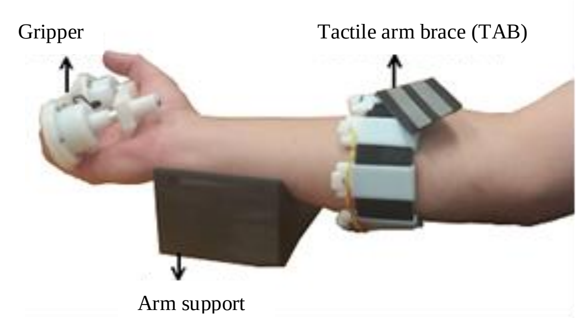

Figure 1 Participant performing gripping motions with the gripping device while wearing the TAB (tactile arm brace).

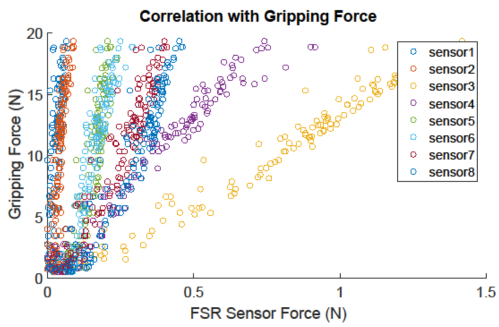

Figure 2 Grip force against TAB sensors contact forces during power gripping.

Detecting Intent

Since there is correlation between the TAB sensor forces and the grip strength being used, the gradient changes in the waveforms will be identified in order to determine whether a gripping motion has been initiated.

The faster it gets detected the quicker a rehabilitative device can assist the hand movement. In order to calculate how quickly the TAB can detect the intent of motion during gripping, a comparison is made between the TAB and the gripping device data.

The eight TAB sensor waveforms and the grip strength waveform were analysed and the instances where change was detected were compared. The cumulative sum algorithm (*cusum*) was slightly modified to detect only positive changes in the data. On both the gripping device data and the TAB data a threshold of 1.5 times the maximum noise amplitude was used in the implementation. The drift parameter was set to half of the threshold.

The *cusum* algorithm can detect the changing points in a waveform and the time where the change had actually began. Thus a threshold was put in place to filter out changes that had occurred at a grip strength of over 0.3kg. This ensured that any positive gradient changes taking place post-gripping were not taken into account. Furthermore, an algorithm was created to form clusters of the data where possible; finding the instances where both the TAB and the grip strength device detect a gripping action. Iterating through each of the eight TAB sensors' detection points the closest gripping indication within 50 samples (0.25s) as indicated by the grip strength waveform was found. Thus, that TAB detection point was assigned to a cluster.

RESULTS

The algorithms used indicated that 92% of the grip detection instances detected by the gripping device were also detected by the TAB. As evident in Figure 3, there were cases where the TAB sensors detected a change but the gripping device did not, or the other way around. Some of those may have been false positives but the high percentage of clustering indicates that overall the algorithm used performs well on the waveforms.
There were 438 gripping instances detected on the gripping device data waveform and for 35 of those there were no TAB sensor change indicators. On the other hand, there were 314 (7.5%) change indications amongst the eight FSR waveforms that could not be clustered with the grip strength device detection points. Within those, only 1.8% could not be clustered together at all.

Visualisation of the distribution of the TAB detection times with respect to the gripping device's respective times, Figure 4, confirms that the TAB detects changes that arise with the initiation of gripping faster than the gripping device. On average the arm brace achieves detection 0.26s (13 data samples) prior to the gripping device. On 2.73% of all 403 common detections the gripping device detected the change before the TAB.

We hypothesise that the proximities of the 8 TAB sensors to certain muscles may affect their individual sensitivities to the various movements as well as the types of gripping. We thus ran the same analysis using only one TAB sensor's data at a time. The results indicated that each sensor detects the changes faster than the gripping device. Nonetheless, there was on average 14% less common detections between with the gripping device and the individual sensors; with three of the sensors in particular indicating a lack of response to gripping, with 22% less common gripping detection instances.

DISCUSSION

The data analysis performed showed that the TAB is slightly more sensitive to muscle contractions than the gripping device used. The faster motion detection by the arm brace suggests that tactile sensing has good potential to recognise motion intent. This may also vary with the speed of the motion.

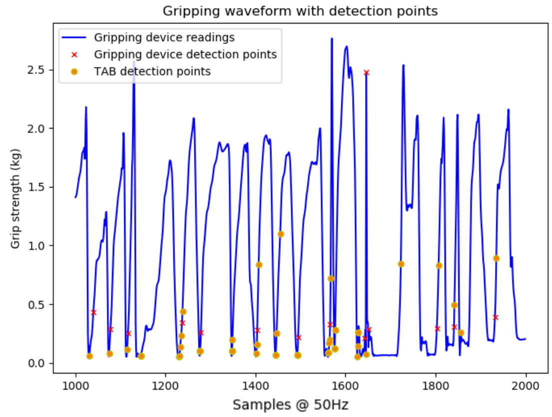

Figure 3 Gripping strength waveform and the detection points of both the gripping device and the TAB sensors.

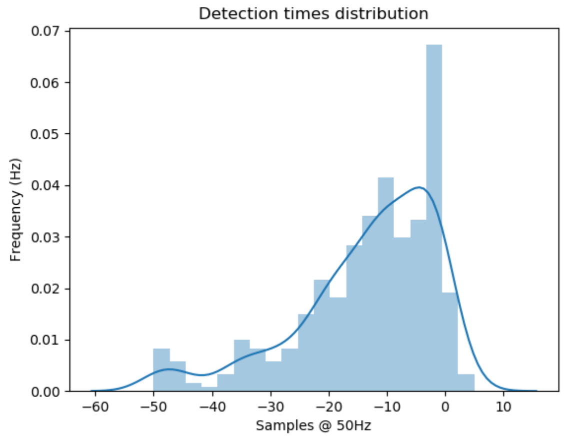

Figure 4 The distribution of the TAB detection points wrt the gripping device detection points (0).

Additionally, the results indicate that the combination of sensing data from all around the forearm is necessary to achieve higher consistency and quicker detection.
Future work will incorporate sonographic imaging which will act as a ground truth. Comparison of the TAB readings to the ultrasound imaging data, will allow for a more accurate evaluation of the TAB response time. In these experiments a variety of motions, and thus muscle contractions, will be looked at. Additionally, the experiments will be repeated using electromyography sensors, thus constructing a good basis from the results for future motion intent recognition systems.

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