PERCEPTUAL AND COMPARATIVE ANALYSES OF A PASSIVE, LINEAR, MULTIPLE DEGREE-OF-FREEDOM SKIN STRETCH DEVICE FOR PROPRIOCEPTIVE SUBSTITUTION

BY

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THESIS

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ABSTRACT

This thesis presents a passive linear skin stretch device and shows that this device can provide multiple degree-of-freedom proprioceptive information about a myoelectric prosthetic hand during grasping. The device consists of three plastic contact pads that are adhered to the skin on the glabrous forearm and that are each attached by a wire to the metacarpophalangeal joint of one prosthetic finger. When a finger rotates about its metacarpophalangeal joint, the attached wire pulls the corresponding contact pad, which stretches the skin to an extent proportional to the angle of rotation. The results of two different studies show that this device can provide proprioceptive information. The first study applies perceptual analysis to show that the structure and dimensionality of the task of interpreting multiple degree-of-freedom proprioceptive information is the same as the structure and dimensionality of the perceptual space that is associated with our passive linear skin stretch device. The second study compares the ability of human subjects to perform a targeting task using our passive linear skin stretch device versus a standard vibrotactile array, and shows that—although both devices result in significantly lower error ($p < 0.05$) than having no feedback—there is no significant performance difference between them. We conclude that our passive linear skin stretch device is a viable alternative to a vibrotactile array.
To my parents who supported me with love and more food than I should eat.

To my newfound friends here and abroad who taught me so much.

To my boyfriend who helped me get through two years from 2186 miles away.

To whatever the future holds - hopefully something good and/or delicious.
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Between 1988 and 1996, there were 18,496 hospital discharges related to upper-limb amputations in the United States of which 5,839 were for trans-radial amputations [1, 2]. In addition, 68.6% of traumatic amputations are upper-limb [1]. In September 2014, the number of US veterans from Iraq and Afghanistan with major limb amputations was 1,573 [3]. Internationally, there are at least 30 million people with amputations in low-income countries [4].

The lack of proprioception, which is the sense enabling a person to know the pose of their joints at any time, has prevented users from accepting their state-of-the-art upper limb prostheses [5, 47, 48]. Because proprioception is necessary for multi-joint coordination [6], simple tasks like throwing a ball become difficult or impossible. One of many proposed solutions is to use a three degree-of-freedom (3-DOF), passive, linear skin stretch device to provide proprioceptive information about the joint angles for the thumb, index, and middle fingers [7]. These fingers completely describe the most commonly used grasps in prostheses because in these grasps, the middle, ring, and pinky fingers move together [8].

The success of our sensory substitution devices depends on the perceptual-cognitive ability of the user to interpret skin stretch as proprioceptive information about the joint angles of the fingers [9]. With this in mind, we performed a perceptual analysis to show that subjects can use our device for proprioceptive substitution in a myoelectric hand.

In addition, we also used a targeting task to demonstrate there is no significant difference in performance when subjects used our passive, linear skin stretch device versus a vibrotactile array, which has been proposed as a proprioceptive substitution device for the opening and closing of a myoelectric hand [10].
1.1 Outline

This thesis presents the results of two different studies, one applying perceptual analysis and the other comparing against a standard vibrotactile array, to show that our passive, linear skin stretch device can be used to provide proprioceptive feedback to users. Chapter 1 reviews sensory substitution devices for proprioception in the literature, introduces the concept of a perceptual space as well as its structure and dimensionality, and provides information about the passive, linear skin stretch device. Then, Chapter 2 explains multidimensional scaling (MDS), the main method used by the haptics community to find the dimensions of the perceptual space. Chapters 3 through 5 provides two lines of evidence that users can interpret multi-DOF linear skin stretch as proprioceptive information. Taking a perceptual-cognitive point of view, Chapter 3 uses MDS and Chapter 4 analyzes a confusion matrix to show that the dimensionality and structure of the perceptual space for skin stretch matches the dimensionality and structure for the task of interpreting skin stretch as joint angles. Chapter 5 shows that linear skin stretch can be used as a proprioceptive substitution device by comparing its performance in single and multi-DOF targeting tasks against both the case of no feedback and vibrotactile feedback, a previously proposed proprioceptive substitution technique. Chapter 6 provides a summary and future work.

1.2 Sensory Substitution Devices for Proprioception in Myoelectric Prostheses

Many sensory substitution devices have been created to supply users with proprioceptive feedback for their upper limb myoelectric prostheses. For example, [10] proposed an eight-motor vibrotactile linear array to convey grasp aperture while unimpaired subjects controlled a virtual hand to reach a target aperture with a mouse wheel. It should be noted that subjects had control and feedback for only a single degree-of-freedom (single-DOF). Another method has been to use rotational skin stretch to relay joint angle information about the elbow [11]. Unimpaired subjects used electromyography (EMG) to control a single-DOF virtual arm to match a target elbow angle. In the realm of multi-DOF proprioceptive feedback, [12] used vibro-
tactile patterns which varied in frequency, location, and amplitude to convey the configuration of a virtual hand performing different grips. Some issues with all of these devices is that they have some combination of requiring large surface area on the skin, high power consumption, and heavy weight. In contrast, the multi-DOF passive, linear skin stretch device uses relatively small surface area, low power consumption, and little weight [7].

1.3 Linear Skin Stretch Device

The passive linear skin stretch device was created to provide proprioceptive feedback information for the joint angles of a prosthetic hand (Fig. 1.1). The device consists of three contact pads, each of which is a 2.54 cm 3D-printed disk adhered to the skin of the glabrous forearm using off-the-shelf No Glue Please! hairpiece tape (Sunshine). Each contact pad is pulled linearly by Spectra 50 lb fishing line connected to the metacarpophalangeal joint of the finger. As a result, when a finger flexes and rotates about its metacarpophalangeal, the contact pad simultaneously moves and stretches the skin linearly according to the joint angle. For a fully flexed finger, the skin is stretched 13 mm. The thumb, index, and middle fingers each have one associated contact pad. The pad for the thumb is adhered on the lateral forearm, the middle is on the medial forearm, and the index is in between. The index contact pad is placed 3 cm proximal to the thumb and middle finger contact pads, so that the three contact pads form a triangle (Fig. 1.2). The device is passive with no additional electronic parts to provide proprioceptive feedback, relying on the existing driving mechanism for the fingers of the prosthetic hand.

For the experiments performed in this thesis, we implemented passive, linear skin stretch with the InMoov robotic arm (Fig. 1.1) [7, 13]. We made and installed custom pulleys for the servos to pull both the fishing lines controlling the joint angles of the fingers and the displacement of the contact pads. The ratio of the radius for finger flexion to the radius for displacement was 13 mm:9.05 mm for the thumb, 13 mm:8.85 mm for the index finger, and 13 mm:8.25 mm for the thumb (Fig. 1.3). We used different ratios because the fingers have different lengths, so the servos sweep through different ranges of angles to fully flex the finger they control. The InMoov is controlled using
an Arduino communicating with MATLAB.

The focus of this thesis is to show that users would be able to interpret proprioceptive information from the skin stretch provided by this device. One of our two studies compared the performance of subjects using skin stretch against both vibrotactile feedback, proposed in [10], and no feedback in a joint angle targeting task. This was to show that there is no significant difference in performance when using the passive, linear skin stretch device versus a standard method of sensory substitution for proprioception.

1.4 Perceptual Space: Dimension and Structure

The other study demonstrated that subjects could use the passive, linear, skin stretch device for proprioceptive feedback by performing a perceptual analysis to find the perceptual space of the device.

The perceptual space is a geometric representation of how stimuli are perceived, so that the salient properties of the stimuli form the dimensions of the space. Stimuli are represented as points in this space and distances between stimuli represent how dissimilar the stimuli are [14, 15]. Larger distances between stimuli mean that the stimuli are more perceptually different, which for a given amount of learning, results in the stimuli being confused less often. Less confusion increases the recognition accuracy over the set of stimuli. The perceptual space has been used to learn about the characteristics people naturally use to discriminate textures [16], musical timbre [17], and vibrotactile stimuli [18]. Knowing the dimensions of the perceptual space can help with stimulus design for applications such as auditory alarms with varying levels of perceived urgency [19] and tactile notifications for mobile devices [20].

In addition, it has been shown that if the dimensionality and structure of the perceptual space for a haptic device matches the dimensionality and structure for the task, then performance with the device for the task will be faster and more accurate compared to when the perceptual space for the device has fewer dimensions and has a different structure [21, 22]. Aligning the perceptual-cognitive abilities of the person to a task by matching the structure and dimensionality of the perceptual space of a sensory substitution device and the task positively impacts the success of the device [9].
There are two types of structure, separable and integral (Fig. 1.4). Separable structure means that trajectories through the perceptual space are constrained to traveling along one dimension at a time and that the perceptual space has a Manhattan distance metric. That is, movement through the perceptual space is a series of step functions (Fig. 1.4a). Integral structure, on the other hand, means that trajectories can travel by changing all of its dimensions simultaneously and that the perceptual space has a Euclidean distance metric (Fig. 1.4b). In other words, it is possible to move through the perceptual space along a diagonal across all dimensions [23].

In the psychophysics and haptics community, the primary method to determine the dimensions of the perceptual space is multidimensional scaling (MDS) [16, 17, 18, 20, 24]. MDS is one method to determine the configuration of stimuli in the perceptual space when only given the dissimilarities or perceptual distances between all pairs of stimuli. It can determine the dimensions of the perceptual space and provide information about relative dissimilarities. To find the perceptual structure, we use a different analysis. In our case, we will analyze a confusion matrix from an identification task to verify the dimensions provided by MDS, in addition to determining the perceptual structure.

Despite the benefits of performing perceptual analysis to match the device to the task at a fundamental perceptual-cognitive level, this analysis is lacking in sensory substitution devices for upper limb prostheses [7, 9, 10, 11, 12]. We start to remedy this issue by performing a perceptual analysis on the passive, linear skin stretch device [7] to see if people can fundamentally interpret skin stretch in terms of proprioceptive joint angle information.

1.5 Possible Dimensionality and Structures for Multi-DOF, Linear Skin Stretch

For the passive, linear skin stretch device, we consider two (of perhaps, many other) possibilities for the dimensions and structure of the perceptual space. Specifically for a device for three fingers, one possibility is that the perceptual space of the device has two dimensions. One dimension could be the combination of displaced contact pads and the second could be the minimum displacement. In this case, the structure is separable because one must deter-
mine the combination of displaced contact pads before setting the minimum. This perceptual space could happen if subjects treat the contact pads for the three fingers as one device with multiple characteristics. In this case, each dimension represents one salient characteristic [18].

Another possibility is the displacement of each contact pad has its own dimension and so the structure is integral because each contact pad can change its displacement independently and simultaneously from the others. This is similar to the perceptual space for images of characters, where the intensity of each pixel has its own dimension [25].

The task for the user of the passive, linear skin stretch device is to interpret the haptic feedback of the device as joint angles for the fingers. The dimensionality of this task is the number of joint angles the user needs to interpret, and the structure is integral because each joint angle can change simultaneously and independently of the others. As a result, in order for our device to be suitable for this task, the perceptual analysis should show that the perceptual space for our device has a dimensionality of three (because we only want the user to know the joint angles for the thumb, index, and middle fingers) and an integral structure. We demonstrate that the device is indeed suitable and that the dimensions of the perceptual space are the displacement of each contact pad and that the structure of the perceptual space is integral. We show this in two ways. First, we show that the perceptual space determined using MDS returns a 3D coordinate frame that strongly correlates with a set of orthogonal axes that represent the normalized amount of skin stretch for each DOF. Second, we show in a grip recognition task that there is a strong correlation ($R^2=0.9$) between classification accuracy between pairs of stimuli and the Euclidean distance between the two stimuli in the perceptual space, suggesting that the dimensions are the displacement of each contact pad and that the structure is integral.
1.6 Figures

Figure 1.1: Passive, linear skin stretch device as implemented with the InMoov arm. Custom pulleys for the servos pulled both the fishing lines controlling the joint angles of the fingers and the displacement of the contact pads. As a result, the pads have a direct mechanical connection to the prosthetic finger.
Figure 1.2: Contact pads. The device consists of three contact pads, each of which is a 2.54 cm 3D-printed disk adhered to the glabrous skin of the forearm using off-the-shelf No Glue Please! hairpiece tape (Sunshine). The pad for the thumb is adhered on the lateral forearm, the middle is on the medial forearm, and the index is in between. The index contact pad is placed 3 cm proximal to the thumb and middle finger contact pads, so that the three contact pads form a triangle.

Figure 1.3: CAD of pulley for the index finger. The larger radius (13 mm) is for the fishing line pulling the finger while the smaller radius (8.85 mm) for the contact pad displacing the skin. The smaller radius on the pulley for the thumb was 9.05 mm and for the middle finger was 8.25 mm.
Figure 1.4: Separable and integral perceptual spaces. (a) Separable perceptual spaces have a city-block distance metric and have staircase trajectories where only one dimension can change at a time. (b) Integral perceptual spaces have a Euclidean distance metric and have trajectories where all dimensions can change simultaneously.
CHAPTER 2
MULTIDIMENSIONAL SCALING (MDS)

In this thesis, we want to find the perceptual space for multi-DOF skin stretch. As a result, we will briefly elaborate on multidimensional scaling, which has been used extensively to find perceptual spaces [16, 17, 18].

2.1 Same Problem, Different Names

The distance geometry problem exists in many fields under many names. Whether it is recognized as graph embedding in computer science [26, 27], multidimensional scaling (MDS) in statistics and psychology [14, 28, 29, 30, 31], or the original distance geometry problem in mathematics and biochemistry [32], finding the coordinates for a set of points (vertices) when only given inter-point distances (edges) is useful for many applications. In fact, it is common for papers presenting new methods to solve the MDS problem to incorporate language and techniques from graph embedding or distance geometry [26, 32, 33, 34, 35, 36].

The procedure for MDS was the first to be created specifically for and applied to the finding of multidimensional perceptual spaces [28, 29]. More recent MDS algorithm derivations refer to work in distance geometry and graph embedding [31, 35, 33, 34].

MDS is a method to create an $M$-dimensional model of the perceptual space so that dissimilarities or perceived differences between stimuli are represented as distances. Coordinates of more dissimilar stimuli are further apart. This is done to find the underlying structure and perceptual dimensions of the perceptual space [14]. MDS begins with a dissimilarity matrix $D$, which is an $N \times N$ matrix of the dissimilarity scores between pairs of $N$ stimuli. Dissimilarity scores $\delta_{ij}$ between stimuli $i$ and $j$ can be found using a separate technique such as cluster-sorting [18, 37]. In general, higher scores
are given to more perceptually different stimuli.

2.2 Classical Multidimensional Scaling

Multidimensional scaling falls under two categories: metric and nonmetric. Metric MDS assumes that the given inter-point distances are Euclidean while non-metric MDS only assumes that the given distances provide correct ordinal information about the relative magnitude of the distances. Both attempt to find the configuration of points in a Euclidean space so that the distances between points in the proposed configuration minimizes the squared error between the distances in the proposed configuration and the given distances. Both methods also require the researcher to use prior knowledge to interpret the dimensions. Although, we will ultimately use nonmetric MDS to find the perceptual space for multi-DOF skin stretch, we will provide a background about metric MDS because it is used to initialize the nonmetric MDS algorithm we use.

Metric or classical multidimensional scaling (CMDS) was first applied to perceptual spaces by Torgeson in 1952 [28] because there were no methods at the time to find perceptual dimensions. Instead, researchers asked subjects to rate stimuli along dimensions that the researchers assumed to be the most relevant to the task at hand. As a result, Torgeson presented an overall procedure including how to find perceptual distances between stimuli to use with MDS and how to use his MDS algorithm. His MDS algorithm is used to find the configuration of points, i.e. the coordinates of stimuli in the perceptual space, when given Euclidean relative distances with error. In CMDS, the terms dissimilarity score (or shortened to dissimilarity) and distance are interchangeable because the dissimilarity matrix is assumed to be Euclidean.

In Torgeson’s formulation of the MDS problem, he assumed that the dissimilarity scores were Euclidean in nature and available for all pairs of points. Specifically, this means that the dissimilarity scores are non-negative and symmetric (i.e. $\delta_{ij} = \delta_{ji}$). Then the dissimilarity matrix, $D = (\delta_{ij})$, is symmetric with non-negative entries and zeros along the diagonal. These assumptions took advantage of the findings of [38], where an algorithm to find the configuration of stimuli from dissimilarities is provided under the assumption that the dissimilarities are error free. For psychophysical data,
the dissimilarities will have error because subjects’ reports will be inconsistent. As a result, Torgeson squared each element of the dissimilarity matrix to get $D^{(2)}$, assumed mean zero error, and added double centering, which is subtracting the row and column means, adding the grand mean of all the elements, and multiplying by $-\frac{1}{2}$. Double centering made $D^{(2)}$ positive semidefinite for use with the algorithm of [38] and to place the origin of the perceptual space at the centroid of all the stimuli, resulting in a unique solution with minimal average error.

Torgeson’s MDS algorithm can be summarized as double centering the matrix of distances to make it positive semidefinite, finding the eigenvalues and eigenvectors of the resulting matrix, and using the subsequent left singular vector and matrix to find the dimensions for the perceptual space. The dimensions with the larger eigenvalues are chosen to be the dimensions of the perceptual space. In other words, the algorithm is as follows [39]:

1. Square each element of the dissimilarity matrix $D$ to get $D^{(2)}$. Note that $D^{(2)} \neq DD^T$.

2. Double center the dissimilarity matrix to get $B = -\frac{1}{2}JD^{(2)}J$, where $J = I - n^{-1}11'$ and $n$ is the number of stimuli.

3. For $B$, find the largest positive eigenvalues $\Lambda$ and the corresponding eigenvectors $E$. If there are negative eigenvalues, this means that the original dissimilarities were not Euclidean or had error. However, as long as the magnitudes of the negative eigenvalues are much smaller than the largest positive eigenvalues, the low dimensional Euclidean model can still be considered a good approximation.

4. The $M$-dimensional configuration of the $n$ stimuli is $X = E_M\Lambda_M^{\frac{1}{2}}$, where $\Lambda_M$ is the diagonal matrix of the $M$ largest eigenvalues of $B$, and $E_M$ is the matrix of their corresponding eigenvectors. Note that because $\Lambda_M$ is diagonal the square root is taken element wise.

It should be noted that this method will yield the same results as principal components analysis if both methods are given a matrix of Euclidean distances.
2.3 CMDS Example

We will now show an example of how to use the classical multidimensional scaling (CDMS) algorithm to find the most salient dimensions of the perceptual space. We will begin with the following dissimilarity matrix, which was generated from a cluster sorting task (see Sec.3.2 for further information about this method of generating dissimilarities) for 18 stimuli:

\[
\begin{pmatrix}
0 & 687.5 & 812.5 & 912.5 & 987.5 & 1000 & 825 & 900 & 1000 & 975 & 1000 & 1000 & 950 & 987.5 & 1000 & 775 & 912.5 & 987.5 \\
687.5 & 0 & 475 & 975 & 837.5 & 925 & 947.5 & 962.5 & 900 & 950 & 975 & 987.5 & 937.5 & 937.5 & 987.5 & 900 & 950 & 900 \\
812.5 & 475 & 0 & 1000 & 962.5 & 912.5 & 9000 & 925 & 1000 & 937.5 & 925 & 987.5 & 862.5 & 925 & 925 & 912.5 & 912.5 \\
912.5 & 975 & 1000 & 0 & 650 & 787.5 & 825 & 862.5 & 1000 & 725 & 887.5 & 925 & 837.5 & 962.5 & 925 & 912.5 & 912.5 & 912.5 \\
987.5 & 837.5 & 962.5 & 650 & 0 & 412.5 & 962.5 & 937.5 & 925 & 850 & 800 & 850 & 812.5 & 862.5 & 925 & 887.5 & 937.5 & 887.5 \\
1000 & 925 & 912.5 & 787.5 & 412.5 & 0 & 962.5 & 975 & 850 & 862.5 & 725 & 750 & 912.5 & 925 & 812.5 & 912.5 & 912.5 & 900 \\
900 & 987.5 & 1000 & 825 & 962.5 & 962.5 & 0 & 512.5 & 875 & 912.5 & 962.5 & 975 & 912.5 & 1000 & 1000 & 875 & 937.5 & 1000 \\
900 & 962.5 & 1000 & 862.5 & 937.5 & 975 & 512.5 & 0 & 675 & 837.5 & 925 & 962.5 & 900 & 975 & 987.5 & 937.5 & 937.5 & 975 \\
900 & 900 & 925 & 1000 & 925 & 850 & 875 & 675 & 0 & 912.5 & 850 & 825 & 1000 & 975 & 962.5 & 987.5 & 987.5 & 987.5 \\
975 & 950 & 1000 & 725 & 850 & 862.5 & 912.5 & 837.5 & 912.5 & 0 & 837.5 & 825 & 587.5 & 825 & 887.5 & 850 & 875 & 862.5 \\
1000 & 975 & 937.5 & 887.5 & 800 & 725 & 962.5 & 925 & 850 & 837.5 & 0 & 487.5 & 900 & 787.5 & 750 & 950 & 937.5 & 812.5 \\
1000 & 987.5 & 925 & 925 & 850 & 750 & 975 & 962.5 & 825 & 825 & 487.5 & 0 & 962.5 & 850 & 562.5 & 975 & 962.5 & 962.5 \\
900 & 937.5 & 987.5 & 837.5 & 812.5 & 912.5 & 912.5 & 900 & 1000 & 875.5 & 900 & 962.5 & 0 & 762.5 & 875 & 712.5 & 825 & 875 \\
987.5 & 937.5 & 862.5 & 962.5 & 862.5 & 925 & 1000 & 975 & 975 & 975 & 825 & 787.5 & 850 & 762.5 & 0 & 662.5 & 925 & 887.5 & 825 \\
1000 & 987.5 & 925 & 925 & 850 & 862.5 & 1000 & 987.5 & 962.5 & 862.5 & 875 & 850 & 762.5 & 875 & 662.5 & 0 & 975 & 875 & 812.5 \\
975 & 900 & 925 & 712.5 & 887.5 & 950 & 875 & 937.5 & 962.5 & 850 & 950 & 975 & 975 & 812.5 & 925 & 925 & 975 & 0 & 550 & 675 \\
912.5 & 950 & 912.5 & 800 & 937.5 & 912.5 & 947.5 & 937.5 & 987.5 & 850 & 950 & 975 & 975 & 812.5 & 925 & 925 & 975 & 0 & 550 & 675 \\
987.5 & 900 & 912.5 & 912.5 & 887.5 & 900 & 1000 & 975 & 962.5 & 862.5 & 812.5 & 862.5 & 875 & 825 & 812.5 & 675 & 687.5 & 0 & 687.5
\end{pmatrix}
\]

We can see this matrix has zeros along the diagonal since stimuli have zero dissimilarity from themselves. As we will see later, the matrix \( B \) generated from \( D \) is not positive semidefinite. This is expected because \( D \) was generated by a cluster sorting task which provides non-Euclidean integer scores related to the dissimilarities between pairs of stimuli. We will continue, however, with this matrix as it is used to initialize the MDS algorithm used when the dissimilarity matrix is non-Euclidean (Sec.2.5). Next, we square each element and double center the dissimilarity matrix to get

\[
B = -\frac{1}{2}JDJ^2
\]

\[
= -\frac{1}{2}(I - n^{-1}11\prime)D(2)(I - n^{-1}11\prime)
\]

(continued on the next page)
Then, the eigenvalue decomposition on $B$ gives us

$$BE = \Lambda E,$$

where

$$\Lambda = \text{diag}(1e5 \begin{pmatrix} 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \end{pmatrix})$$

and

$$E = \begin{pmatrix} -0.06 & -0.24 & -0.23 & 0.07 & 0.16 & -0.05 & -0.31 & -0.30 & 0.09 & -0.33 & 0.27 & -0.23 & 0.49 & -0.02 & 0.01 & 0.06 & 0.21 & -0.39 \\ 0.28 & -0.24 & 0.33 & -0.33 & -0.29 & 0.05 & 0.07 & -0.04 & 0.19 & 0.14 & 0.00 & -0.09 & -0.13 & 0.16 & 0.19 & 0.16 & 0.46 & -0.25 \\ -0.25 & -0.24 & -0.19 & 0.29 & 0.24 & -0.22 & 0.11 & 0.33 & -0.24 & 0.25 & -0.32 & 0.06 & -0.08 & 0.08 & 0.03 & 0.20 & 0.50 & -0.16 \\ 0.26 & -0.24 & -0.17 & 0.17 & 0.22 & 0.06 & 0.23 & -0.36 & -0.21 & 0.31 & -0.40 & -0.02 & 0.25 & 0.06 & 0.34 & -0.04 & -0.32 & 0.06 \\ -0.51 & -0.24 & -0.18 & 0.16 & -0.31 & 0.17 & 0.08 & -0.11 & 0.06 & 0.00 & 0.22 & -0.24 & -0.07 & -0.04 & 0.57 & -0.05 & -0.06 & 0.15 \\ 0.38 & -0.24 & 0.24 & 0.06 & 0.25 & -0.30 & -0.29 & 0.26 & 0.15 & -0.26 & 0.01 & 0.16 & -0.03 & 0.14 & 0.47 & -0.10 & 0.04 & 0.26 \\ -0.09 & -0.24 & -0.02 & 0.37 & -0.24 & -0.32 & 0.08 & 0.38 & 0.08 & 0.19 & 0.11 & 0.26 & 0.28 & 0.04 & -0.14 & -0.41 & -0.12 & -0.30 \\ 0.13 & -0.24 & 0.17 & 0.54 & 0.13 & 0.41 & -0.10 & -0.04 & 0.07 & 0.14 & -0.01 & 0.17 & -0.11 & -0.02 & -0.20 & -0.49 & -0.08 & -0.23 \\ -0.09 & -0.24 & -0.15 & -0.27 & 0.08 & -0.16 & 0.16 & -0.31 & -0.12 & -0.37 & -0.08 & -0.10 & -0.52 & 0.15 & -0.11 & -0.41 & 0.19 & 0.00 \\ -0.25 & -0.24 & 0.19 & 0.01 & -0.11 & -0.26 & -0.39 & -0.06 & 0.16 & -0.27 & -0.46 & -0.15 & -0.41 & -0.02 & -0.04 & -0.27 & 0.06 \\ -0.16 & -0.24 & 0.18 & -0.23 & 0.26 & 0.27 & -0.13 & 0.16 & -0.45 & 0.23 & -0.38 & -0.28 & 0.10 & 0.12 & -0.07 & 0.09 & 0.07 & 0.35 \\ 0.29 & -0.24 & -0.24 & 0.30 & -0.49 & -0.04 & 0.20 & 0.08 & 0.04 & -0.01 & -0.08 & -0.35 & 0.23 & 0.16 & -0.15 & -0.11 & 0.14 & 0.39 \\ 0.18 & -0.24 & -0.32 & -0.07 & 0.20 & 0.20 & 0.28 & 0.37 & 0.05 & -0.29 & 0.18 & -0.10 & -0.14 & -0.50 & -0.04 & 0.14 & -0.31 & -0.03 \\ 0.22 & -0.24 & 0.06 & 0.03 & -0.17 & -0.23 & -0.12 & -0.34 & -0.36 & 0.03 & 0.17 & 0.47 & 0.00 & -0.39 & -0.26 & 0.19 & 0.04 & 0.20 \\ -0.30 & -0.24 & 0.22 & -0.13 & 0.22 & 0.18 & 0.19 & -0.07 & 0.40 & -0.20 & -0.32 & 0.23 & 0.31 & -0.02 & -0.29 & 0.10 & 0.08 & 0.34 \\ -0.09 & -0.24 & 0.52 & 0.24 & -0.06 & -0.22 & 0.42 & -0.03 & -0.17 & -0.18 & 0.15 & -0.15 & -0.02 & 0.25 & -0.02 & 0.28 & -0.27 & -0.25 \\ -0.02 & -0.24 & -0.15 & -0.12 & -0.25 & 0.29 & -0.44 & 0.19 & -0.21 & -0.23 & -0.01 & 0.14 & -0.11 & 0.36 & -0.13 & 0.30 & -0.02 & -0.13 \\ 0.07 & -0.24 & -0.25 & -0.01 & 0.16 & -0.13 & -0.03 & -0.12 & 0.46 & 0.42 & 0.30 & 0.04 & -0.29 & 0.34 & -0.18 & 0.30 & -0.08 & 0.06 \end{pmatrix})$$
input dissimilarities are not Euclidean, as expected by how \( D \) was generated. When CMDS is used for model reduction however, as long as the magnitude of the negative eigenvalues are relatively small, then the dimensions associated with the positive eigenvalues can be used to reduce the dimensionality of the data, starting with the dimension associated with the largest eigenvalue.

For the sake of illustration, we will proceed to show how one would go about finding the configuration of the points if it were clear from the eigenvalues. As we will show later using non-metric MDS, 3 is indeed the number of dimensions for the perceptual space for the dissimilarity matrix. In addition, the result presented will be used to initialize the non-metric MDS algorithm. In the 3D space, the stimuli configuration \( X \) is given by

\[
X = E_3 \Lambda_3^{\frac{1}{2}} = (\text{continued on the next page})
\]
\[ X = \begin{pmatrix} -0.3876 & 0.2101 & 0.0634 \\
-0.2528 & 0.4558 & 0.1618 \\
-0.1565 & 0.5024 & 0.2022 \\
-0.0639 & -0.3229 & -0.0383 \\
0.1550 & -0.0643 & -0.0452 \\
0.2608 & 0.0391 & -0.0996 \\
-0.2953 & -0.1174 & -0.4059 \\
-0.2337 & -0.0784 & -0.4883 \\
-0.0048 & 0.1949 & -0.4086 \\
0.0554 & -0.2729 & -0.0381 \\
0.3515 & 0.0745 & -0.0949 \\
0.3934 & 0.1415 & -0.1105 \\
-0.0314 & -0.3050 & 0.1360 \\
0.1967 & 0.0385 & 0.1872 \\
0.3432 & 0.0764 & 0.0959 \\
-0.2528 & -0.2661 & 0.2847 \\
-0.1329 & -0.2230 & 0.2976 \\
0.0557 & -0.0830 & 0.3006 \end{pmatrix} \]

\[ = 1e3 \begin{pmatrix} 1.0973 & 0 & 0 & 0 & \cdots & 0 \\
0 & 1.0000 & 0 & 0 & \cdots & 0 \\
0 & 0 & 0.9944 & 0 & \cdots & 0 \end{pmatrix}_{3 \times 18} \]

\[ = 1e3 \begin{pmatrix} -425.25 & 210.09 & 63.08 & 0 & \cdots & 0 \\
-277.40 & 455.77 & 160.88 & 0 & \cdots & 0 \\
-171.76 & 502.39 & 201.09 & 0 & \cdots & 0 \\
-70.07 & -322.91 & -38.07 & 0 & \cdots & 0 \\
170.04 & -64.35 & -44.92 & 0 & \cdots & 0 \\
286.15 & 39.13 & -99.03 & 0 & \cdots & 0 \\
-323.97 & -117.40 & -403.61 & 0 & \cdots & 0 \\
-256.45 & -78.43 & -485.59 & 0 & \cdots & 0 \\
-5.26 & 194.90 & -406.26 & 0 & \cdots & 0 \\
60.81 & -272.90 & -37.84 & 0 & \cdots & 0 \\
385.66 & 74.52 & -94.39 & 0 & \cdots & 0 \\
431.63 & 141.45 & -109.91 & 0 & \cdots & 0 \\
-34.49 & -305.03 & 135.23 & 0 & \cdots & 0 \\
215.88 & 38.49 & 186.11 & 0 & \cdots & 0 \\
376.54 & 76.42 & 95.34 & 0 & \cdots & 0 \\
-277.37 & -266.12 & 283.07 & 0 & \cdots & 0 \\
-145.80 & -223.02 & 295.96 & 0 & \cdots & 0 \\
61.13 & -83.01 & 298.87 & 0 & \cdots & 0 \end{pmatrix}_{18 \times 18} \]
which is shown as the Torgerson points in Fig. 2.2.

The translation and rotation of axes provided by CMDS are arbitrary because the matrix of dissimilarities are inter-point distances rather than absolute positions. For interpretive purposes, a more meaningful set of axes of the same number of dimensions can be imposed on the final configuration.

2.4 Non-Metric Multidimensional Scaling: Kruskal’s Stress-1 Criterion

In the non-metric multidimensional scaling formulation presented by Kruskal and Shepard [15, 30], the dissimilarities are no longer taken to be Euclidean. In Classical MDS, the dissimilarities served directly as the Euclidean distances in the configuration, and so, the term dissimilarity and distance could be used interchangeably. This is no longer the case. In non-metric MDS, the assumption is now that dissimilarities and distances are related to each other through a monotonic function. That is, the dissimilarities provide ordinal rather than absolute information about the inter-point distances between pairs of stimuli in the perceptual space. For example, during a cluster sorting task, dissimilarity $\delta_{ij}$ between stimuli $i$ and $j$ is constrained to a set of integers. Given a matrix of dissimilarities, non-metric MDS iteratively moves the coordinates of stimuli in an $M$-dimension perceptual space so that the Euclidean distance $d_{ij}$ between the stimuli $i$ and $j$ minimizes a stress criterion, a badness-of-fit measure between the distances among the stimuli in the perceptual space and a monotonic function of dissimilarities. The algorithm by which it moves the coordinates varies by the software running the non-metric MDS algorithm. For example, MATLAB’s `mdscale` initializes the search using Torgerson’s algebraic algorithm and iterates using a gradient descent method. ALSCAL instead initializes using an algebraic solution from [40] iterates using alternating least squares [41, 42].

Many non-metric MDS algorithms differ from each other by changing the stress criterion [14], but the first and the one we will ultimately use is Kruskal’s Stress-1 Criterion [30], which is

$$Stress-1 = \sqrt{\frac{\sum_{i=1}^{N} \sum_{j=i+1}^{N} (f(\delta_{ij}) - d_{ij})^2}{\sum_{i=1}^{N} \sum_{j=i+1}^{N} d_{ij}^2}},$$
where $d_{ij}$ is the Euclidean distance between $i$ and $j$ in an $M$-dimensional perceptual space, $\delta_{ij}$ is the non-Euclidean (ordinal) dissimilarity between $i$ and $j$, and $f(\cdot)$ is a monotonic function used to scale the dissimilarities, so they can be compared to $d_{ij}$.

The minimization is repeated for various dimensions $M$. Higher dimensional models will result in smaller minimized stress criteria but at the risk of becoming difficult to interpret. While CMDS considered the largest eigenvalues to determine the number of dimensions, non-metric MDS considers the trade-off between decreasing the stress criterion and increasing the number of dimensions. The ultimate number is chosen based on when the returns on decreasing the stress criterion start to diminish as $M$ increases. This point is referred to as the knee in a scree plot of stress versus dimension.

Finally, an MDS plot is generated with the chosen number of dimensions. The coordinate frame in which the MDS algorithm minimizes the stress criterion has an arbitrary orientation and scaling. As a result, it is left to the researcher to consider the configuration of stimuli in the perceptual space and interpret the dimensions of the perceptual space in terms of meaningful physical characteristics of the stimuli.

2.5 Non-metric MDS (Stress-1) Example

We show how non-metric MDS using the stress-1 criterion can be performed on the dissimilarity matrix $D$ (Eq. 2.1) to find the perceptual dimensions. The data in $D$ was collected using a cluster sorting task, so it is non-Euclidean, ordinal data, and as a result, finding the dimensions of the perceptual space using non-metric MDS is more appropriate than with CMDS [43]. Non-metric MDS applies a monotonic transformation to the dissimilarities to make it possible to find the difference against Euclidean distances [39]. In MATLAB’s implementation of a non-metric MDS solver, the monotonic function computes $f(\delta_{ij})$ as the values closest to the current inter-point Euclidean distances between stimuli in the $M$-dimensional perceptual space, in the least squares sense, while constrained to be monotonic in the given dissimilarities.

Once, the transformation is performed, the initial configuration is found. In MATLAB’s implementation of non-metric MDS using stress-1 `mdscale`,
the MDS algorithm initializes the search space using the configuration for $M$-dimensions provided by CMDS. It does this by using the $M$-eigenvectors of the largest $m$ eigenvalues to find the initial configuration for the $m$-dimensional space (Fig. 2.2). Another option is to use multistart, where the initial configuration is randomly generated for multiple runs through the entire MDS solver, to help find the global, rather than local minimum [14].

Once there is a starting configuration, the next step is to use it to begin minimizing the stress-1 criterion. The minimization algorithm depends on the choice of MDS solver. The source code of mdscale reveals that it uses a nonlinear conjugate gradient descent method with Polak-Ribiere’s formula to compute the descent direction during a line search. Figure 2.2 shows how the configuration changes from the initial result provided by Torgerson’s CMDS to the final results provided by Kruskal’s non-metric, stress-1 MDS algorithm. Generally, lower dimensional spaces require fewer iterations before the change in stress-1 is below the tolerance for the minimization algorithm but also result in larger minimum stress-1.

While only 3 dimensions are illustrated in Fig. 2.2, we used mdscale to find the configuration and minimum stress for up to seven dimensions. We need to consider enough dimensions to see where the minimum stress begins to decrease more slowly as a function of the number of dimensions. This is seen as a bend (known as the knee) in the scree plot like in Fig. 2.3. This plot is known as a scree plot because it resembles a profile of a hill where the debris at the base is known as scree, and we choose the number of dimensions based on where the scree begins. In this example, the knee is at 3 dimensions, and the associated stress is 0.1090.

### 2.6 Multidimensional Scaling in Haptics

The haptics community has used MDS to optimize vibrotactile stimuli [18] as well as find the perceptual dimensions of textures [44].

To use MDS (Fig. 2.4), the first step is to find the dissimilarity matrix. There are many ways to do this. When Torgerson first introduced MDS, he suggested having subjects compare triads of stimuli [28]. Another way is to present subjects pairs of stimuli, ask them to rate on a numerical scale (e.g. 0-8) how similar the objects are, and then linearly scale those ratings
(e.g. 8-0) so that more similar objects have lower scores. One final example is to use Ward’s Cluster Sorting Task [37], which was used when MDS was first introduced to the haptics community as a tool to help improve the discriminability of vibrotactile stimuli [18]. This is the method we use in our analysis of multi-DOF skin stretch.

Once the dissimilarity matrix is found, it is given to an MDS solver, which is asked to solve the MDS problem for multiple possible dimensionalities. Based on the location of the knee in the scree plot, the dimensionality of the MDS plot will be chosen and interpreted by the researcher based on prior knowledge. In some cases, not all dimensions will be interpretable [44] and in general, it is easier to decipher lower dimensional plots.
2.7 Figures

Figure 2.1: Normalized eigenvalues from CMDS in descending order.

Figure 2.2: Comparison of stimuli configuration for classical and non-metric MDS. The arrows show how the non-metric MDS algorithm implemented by MATLAB changes the initial configuration provided by classical MDS.
Figure 2.3: Scree plot for non-metric MDS with stress-1 using *mdscale* for the current example. The knee, or bend in the plot, is at 3 dimensions, so the perceptual space is 3D.

Figure 2.4: MDS process in haptics.
CHAPTER 3

PERCEPTUAL DIMENSIONS OF 3-DOF SKIN STRETCH ACCORDING TO MDS

In this chapter, we find the dimensionality of the perceptual space for the multiple degree-of-freedom (multi-DOF) skin stretch device using MDS and then interpret the meaning of the dimensions. To use multidimensional scaling (MDS) to find the dimensions of the perceptual space for multi-DOF skin stretch, we must first find the dissimilarities between pairs of skin stretch stimuli. One way to find these dissimilarities is to first score how similar the stimuli pairs are and then linearly scale these similarity scores into dissimilarity scores.

We determined the similarity scores using Ward’s Cluster Sorting Task [37, 18], where subjects were asked to sort skin stretch stimuli into a given number of clusters based on the similarity between the stimuli. We recorded how often stimuli were sorted together to generate similarity scores and linearly scaled these scores to dissimilarity scores so that lower similarity scores would correspond to larger dissimilarities scores. The dissimilarity scores were used as ordinal information about the perceptual distances between skin stretch stimuli for MDS, which showed that the perceptual space for the 3-DOF linear skin stretch device is 3D, one for each DOF. This is desirable because each DOF for the linear skin stretch device is used to provide information about one joint angle. As a result, the dimensionality of the perceptual space of the device and task of interpreting multi-DOF skin stretch feedback as multi-DOF proprioception are the same. Once we complete our perceptual analysis in Ch. 4 to also show that the structure of the perceptual space for the device is the same as that for the task, then we will have demonstrated that users can use the multi-DOF skin stretch device to gain proprioceptive information about multiple joint angles from a perceptual-cognitive point of view.

In addition to finding the number of dimensions of the perceptual space for the skin stretch device using MDS, we also interpreted the dimensions
by fitting a set of orthogonal axes to the MDS plot. We found that each dimension corresponded to the displacements of the contact pads for each DOF of the skin stretch device. This interpretation is used in Ch. 4 to find the perceptual structure for our device.

3.1 Experimental Setup

Six naive, unimpaired subjects, 5 male, 1 female (ages: 19-27), volunteered for this experiment, which took place in one 90-minute session. All data were collected and processed using MATLAB. In addition, all procedures and equipment were approved by the Institutional Review Board of the University of Illinois at Urbana-Champaign. Subjects placed their left forearms, palm up, underneath an elevated InMoov arm [13], and slipped their hand under a handle to prevent their arm from moving over the course of the experiment. Three contact pads were adhered to their forearms in order to provide skin stretch.

The goal of this experiment was to find the perceptual space for the skin stretch device by sorting different patterns of skin stretch stimuli without association to joint angles. The InMoov arm, including the hand, and the contact pads were obscured from view during the experiment. Subjects wore headphones playing pink noise to remove auditory cues.

Because subjects needed to heavily use a computer mouse to cluster 63 different skin stretch stimuli, they felt skin stretch stimuli on their left forearm, so they could use the mouse with their right hand. Despite the InMoov arm being a right arm, presenting stimuli on the left arm was acceptable because we did not ask them to associate the stimuli to joint angles, only to compare the sensation of different skin stretch stimuli. The InMoov was hidden from view so subjects were unaware of the mismatch in handedness.

Although subjects were not told about any association between the contact pads and joint angles, we have the motivation to eventually use the contact pads to convey joint angles. As a result, for clarity, we refer to each contact pad by the finger to which they will correspond. The pad for the thumb was adhered on the lateral forearm, the middle on the medial forearm, and the index in between. The index finger contact pad was placed 3 cm proximal to the thumb and middle finger contact pads, so that the three contact pads
formed a triangle. As a result, a skin stretch stimulus can be described by a
triplet representing the displacement of the thumb, index, and middle fingers’
contact pads. Subjects did not know about this description for the stimuli.

3.2 Cluster Sorting Task

We began with the cluster sorting MDS experiment as performed in [18] to
determine the perceptual dimensions subjects used to discriminate various
patterns of 3-DOF, linear skin stretch stimuli. Cluster sorting is faster than
asking subjects to explicitly provide a similarity score for all possible pairs
of stimuli but results in the same dimensions (but not absolute scale) for the
perceptual space after the data is converted to dissimilarity scores and given
to MDS [37].

Our set of stimuli consisted of permutations of the displacements for three
contact pads, where the distances could be 0, 33, 66, and 100% of the possible
13 mm range. We did not present the stimulus where all contact pads were at
0% because this easily identified stimulus would distort the resulting model
of the perceptual space [18]. As a result, we presented a total of 63 stimuli.

For this experiment, we created a GUI based on [18]. 63 stimuli were
represented by 63 numbered boxes, which were assigned randomly and pre-
sented in a random order on-screen. The correspondence between the num-
ber and stimulus was consistent for the subject during the entire duration of
the experiment. A subject could feel a stimulus by right-clicking on a box,
which would present a skin stretch stimulus for 2 seconds before returning
to (0,0,0)% . To sort a stimulus into a cluster with other similar stimuli, the
subject dragged the numbered box into one of the larger boxes representing
clusters. Text boxes were available for the subject to label the clusters if they
needed help remembering how the sorted stimuli were related each other. In
the first trial, the subject could click on the buttons within “Select Number
of Boxes” to change the number of clusters; in other trials, these buttons
were removed. Once the subject finished sorting all stimuli into all clusters
for one trial, he or she pressed “Exit Sort” to proceed.

Subjects were asked to undergo five trials of cluster sorting. In the first
trial, subjects sorted stimuli into as many clusters as they desired, up to 15.
Then, subjects were asked to sort into a specified number of clusters for the
remaining four trials based on the number of clusters they had naturally used in the first trial. In this experiment based on [18], the number of clusters for the last four trials came from a set of \{3, 6, 9, 12, 15\}. The element closest to the number of clusters in the first trial was removed. Then, subjects were told to sort into the remaining numbers of clusters, which were asked for in a random order. For example, if a subject had sorted the skin stretch stimuli into 7 clusters, then 6 would be removed and the subject would be asked to sort into groups of \{3, 9, 12, 15\} in a random order for the remaining 4 trials.

3.3 Preparing Data for MDS

First, we created a symmetric 63x63 similarity matrix from the results of the Cluster Sorting Task. Elements \(ij\) and \(ji\) of the matrix were determined by the number of clusters that subjects were sorting into at the time that stimuli \(i\) and \(j\) were put into the same cluster. For example, if stimuli \(i\) and \(j\) were in the same cluster when the subject was sorting into 3, 12, and 15 clusters, the elements \(ij\) and \(ji\) in the similarity matrix will be \(3 + 12 + 15 = 30\). Note that if the first number of clusters chosen by the subject is not from \{3, 6, 9, 12, 15\}, then the closest number is used instead, so that the maximum possible element in the similarity matrix is \(3 + 6 + 9 + 12 + 15 = 45\). Finally, the similarity matrix with elements from 0-45 was linearly scaled to a dissimilarity matrix with elements from 1000-0.

3.4 Using MDS to Find the Number of Dimensions

The dissimilarity matrix was given to MATLAB’s MDS solver \textit{mdscale}, which uses a nonlinear conjugate gradient descent method with Polak-Ribiere’s formula to compute the descent direction during a line search. We used the default settings for \textit{mdscale}, which uses Kruskal’s normalized stress1 criterion, initializes the search with the classical MDS solution, and has a maximum number of iterations of 200, a termination tolerance for the stress criterion and the relative norm of its gradient to be \(1e^{-4}\), and a termination tolerance for the norm of the step size for the line search to be \(1e^{-4}\). For our analysis,
the only cause for termination was that the relative norm of the gradient of the stress criterion was smaller than the termination tolerance. The outputs of the solver were the coordinates of all the stimuli and the final, minimum stress criterion for an $M$-dimensional space, which we repeatedly found for $M = 1$ through $M = 5$.

We plot the final stress criterion vs. the number of dimensions in a scree plot (Fig. 3.3). We can see that the knee of the plot is at 3 dimensions. As a result, we now know that the perceptual space can be modeled using 3 dimensions, although we do not know yet what they represent. To interpret the dimensions, we examine the 3D MDS plot, which shows the configuration of skin stretch stimuli which minimized the stress criterion in a 3D space.

### 3.5 Interpreting the Three Dimensions

A 3D MDS plot (Fig. 3.4) depicts the coordinates of the stimuli in a 3D space. In any MDS plot created using information from the Cluster Sorting Task, only dimensions and the ordinality of inter-point distances can be interpreted. In the MDS plot for skin stretch stimuli, each stimulus consists of a triplet of three displacements for each contact pad. The displacement of contact pad T (thumb) is represented by the size of the marker, contact pad I (index) by the color, and contact pad M (middle) by the shape. For example, for the largest brown triangle, the stimulus is 100% of the 13 mm range for displacement. The dimensions used by mdscale to minimize the stress criterion are arbitrary and can be freely rotated and scaled.

To interpret the dimensions, we used a process similar to [18], which projected dimensions onto the MDS plot which reflected the input parameters for the device generating their vibrotactile stimuli. In the case of [18], the parameters were frequency, amplitude, and waveform. In our case, the input parameters to the skin stretch device were the displacements of the contact pads for each finger. As a result, we began by finding the points that would define the dimension representing the displacement for the thumb contact pad. We found the centroids of all stimuli where the thumb contact pad was at 0% displacement out of a 13 mm range, then at 33%, 66%, and 100%, for a total of 4 centroids. Next, we repeated this process to find the centroids that would define the dimensions representing the displacements for the in-
dex and middle contact pads. Then, we found the set of orthogonal axes with minimal error between the centroids and their associated dimensions.

To fit orthogonal axes to the three sets of displacement centroids, we wanted to find lines of the form \( L_i(t) = v + tw_i, \ i = 1, 2, 3 \) (for the displacements of the contacts pads for the thumb, index, and middle fingers, respectively), such that the residual distance between the data in each set and its respective line was minimized. In this expression, \( v \) and \( w_i \) were 3D vectors. Recall that the minimum distance between a point \( p \) and a line \( L(t) = x_0 + tx \) can be expressed as

\[
d = \frac{|(p - x_0) \times (p - x_0 - x)|}{|x|}
\]

To enforce orthogonality of the axes, we required \( w_1 \cdot w_2 = w_2 \cdot w_3 = w_3 \cdot w_1 = 0 \). We thus had the constrained nonlinear optimization problem

\[
\begin{align*}
\min_{v, w_1, w_2, w_3} & \quad \sum_{i=1}^{3} \sum_{j=1}^{4} \frac{|(p_i^j - v) \times (p_i^j - v - w_i)|}{|w_i|} \\
\text{subject to} & \quad |w_i \cdot w_j| = 0, \ \text{for} \ i, j = 1, 2, 3, \ i \neq j
\end{align*}
\]

where \( p_i^j \) denotes the \( j^{th} \) data point in the set corresponding to the \( i^{th} \) axis.

This optimization problem was solved using the MATLAB function \( \text{fmincon} \). The minimum was found to be

\[
\begin{align*}
v &= \begin{bmatrix} -3.234 \\ -0.810 \\ 6.258 \end{bmatrix} & w_1 &= \begin{bmatrix} -0.234 \\ -0.777 \\ -0.584 \end{bmatrix} \\
w_2 &= \begin{bmatrix} 0.072 \\ 0.776 \\ -0.627 \end{bmatrix} & w_3 &= \begin{bmatrix} 0.990 \\ -0.137 \\ -0.037 \end{bmatrix}
\end{align*}
\]

with a minimizing value of 294.4. At this solution, the average violation of each orthogonality constraints was 0.123.

To quantify how well this set of orthogonal axes fit the data, the best fit line was computed for each of the three sets of data independently without enforcing the orthogonality constraint. The angles between the unconstrained and constrained best fit lines were found by computing the cross product of
and a unit vector aligned with the unconstrained best fit line, and then taking the arcsine of the norm of this vector. These angles were 1.55°, 4.89° and 1.23° for $i = 1$ (thumb), 2 (index), and 3 (middle), respectively. The mean of each of the three sets of data was offset from the origin $v$ of the orthogonal frame by a distance of 7.11.

The best fit orthogonal axes as well as the individual best fit lines for the displacement centroids of each contact pad are shown in (Fig. 3.5).

3.6 The Perceptual Dimensions of 3-DOF Skin Stretch

The MDS analysis of the Cluster Sorting Task showed that the perceptual space can be represented with 3 dimensions. As a result, we eliminated any possible 1D or 2D perceptual spaces, such as a 1D space where subjects only use the maximum displacement to distinguish skin stretch stimuli or a 2D space where subjects use the combination of which contact pads are moving and the minimum displacement of the moving contact pads.

To interpret the 3 dimensions, we began by considering the input parameters for our skin stretch device, i.e. the individual contact pad displacements for each DOF. As a result, we found 3 sets of 4 centroids in order to describe the dimensions of the perceptual space in terms of the contact pad displacements for each finger. Once we found the centroids for each finger, we projected an orthogonal set of axes onto the space, where each axis is related to the displacement of a contact pad. The fit of the orthogonal axes onto the space is good because the deviations of 1.5, 4.9, and 1.2 ° from the 3 unconstrained best fit lines through the centroids of the displacements for the individual contact pads are small.

This provides one piece of evidence that subjects could interpret 3-DOF skin stretch as 3-DOF proprioceptive information about 3 fingers, since matching the dimensionality of the perceptual space for the feedback device and the task improves task speed and accuracy [21, 22]. In addition, the fact that each dimension of the perceptual space for the skin stretch device is the displacement of a single contact pad representing one joint angle suggests that this result could be extended to additional degrees-of-freedom by introducing a new contact pad for each additional joint angle we want to give to the subject.
It should be noted that while we have found the perceptual dimensions, we have not found the perceptual structure. That is, we do not know if subjects perceived the displacements of all contact pads simultaneously or only along one dimension at a time.
3.7 Figures

Figure 3.1: Experimental setup for Cluster Sorting Task. Subjects placed their left forearms, palm up, underneath the elevated InMoov arm, and slipped their hand under a handle to prevent their arm from moving over the course of the experiment. Three contact pads were adhered to their forearms in order to provide skin stretch. The arm and contact pads were obscured from view during the experiment, and subjects wore headphones to remove auditory cues.
Figure 3.2: GUI for Cluster Sorting Task. Based on [18], this GUI was used to allow subjects to sort skin stretch stimuli into clusters based on similarity. To feel a skin stretch stimulus, subjects right-clicked on one of 63 numbered green boxes, which represented the 63 stimuli. Some stimuli are shown sorted into the larger boxes, representing the clusters. Subjects were also provided with blank text boxes they could optionally use to help them remember their sorting criteria; text is displayed in the labels here for illustrative purposes. “Select Number of Boxes” was only visible on the first trial when subjects sorted stimuli into however many clusters they felt was natural for the skin stretch stimuli.
Figure 3.3: Scree plot for MDS of dissimilarity matrix from Cluster Sorting Task with 3-DOF linear skin stretch. The knee in the plot suggests the perceptual space for 3-DOF linear skin stretch has 3 dimensions.
Figure 3.4: 3D MDS plot from Two Perspectives. Each stimulus consists of a set of three displacements for each contact pad, represented by one marker in the plot. The displacement of contact pad T (thumb) is represented by the size of the marker, contact pad I (index) by the color, and contact pad M (middle) by the shape. In general, displacement for the thumb appears to increase along one axis (clustered by size), index along another (clustered by color), and middle along a third (clustered by shape). Dimensions assigned by the MDS solver are arbitrary.
Figure 3.5: Displacement centroids, their best fit lines (dashed), and best fit orthogonal axes (solid). To find a displacement centroid, we found the centroid of all skin stretch stimuli in the MDS plot (Fig. 3.4) where the contact pad for one finger had a given displacement. We did this for all combinations of fingers and displacements to find all centroids. Then, we found the 3 best fit lines to the centroids for the contact pads of individual fingers. We also fit a set of axes to the centroids with the constraint that the axes share a common origin and be orthogonal. There is little offset (7.11) between the origin of the orthogonal axes from the mean of the unconstrained best fit lines for the sets of centroids for the displacements of each finger. Additionally, small angular deviations of 1.5° (Thumb), 4.9° (Index), and 1.2° (Middle) between the orthogonal and unconstrained axes suggest the perceptual space for multi-DOF skin stretch stimuli can be represented by an orthogonal set of axes where each dimension is the displacement of a contact pad.
CHAPTER 4

PERCEPTUAL STRUCTURE ACCORDING TO THE CONFUSION MATRIX

While multidimensional scaling (MDS) as used by the haptics community provides information about the dimensions of the perceptual space for multiple degrees-of-freedom (multi-DOF) linear skin stretch, it does not tell us if the structure of the perceptual space for the device is integral or separable. To find the structure as well as validate our interpretation of the perceptual dimensions from MDS, we studied the ability of subjects to identify grasps from 3-DOF skin stretch stimuli [45]. To do this, we analyzed the confusion matrix of the Grip Recognition Task, where subjects were passively presented with skin stretch stimuli and asked to identify the associated grasp [7].

The order of the most confused grasps is different when the perceptual structure for skin stretch stimuli is integral versus separable because the two types of perceptual structure use different distance metrics. We found that Euclidean distances could predict the order of decreasingly confused grasps better than Manhattan distances. We then demonstrate that a logistic function of Euclidean distances between stimuli in the perceptual space can predict identification accuracy ($R^2 = 0.90$ and 46.8% (near 50% chance) accuracy at zero distance). We used a logistic function because by the definition of a perceptual space, stimuli which are further apart are less likely to be confused but identification accuracy cannot exceed 100%.

As a result, we now see the perceptual space for the skin stretch device has an integral structure and one dimension per contact pad. In addition, the task of interpreting multi-DOF skin stretch as multi-DOF joint angles has one dimension for each joint angle because each joint angle can change independently and an integral structure because all joint angles can change simultaneously. Since we now know that dimensionality and structure are the same for the task and the perceptual space of the device, we can conclude that the multi-DOF skin stretch device can be used for proprioceptive feedback [9] from a perceptual-cognitive point of view. Also, it will perform faster and
more accurately than any sensory substitution device for proprioception that does not have a perceptual space with one dimension per joint angle and an integral structure [21, 22].

4.1 Grip Recognition Task

Eleven unimpaired subjects, 7 male, 4 female (ages:19-30) volunteered for this experiment. 2 males had performed the cluster-sorting task immediately before this experiment. Data for 5 subjects came from [7]. This task took place over a single 20 minute session.

This experiment was identical to the Grip Recognition Task presented in [7], but with a modified test setup. In [7], it was possible for subjects to feel vibrations through the wrist brace and the plastic block attaching the InMoov arm to the wrist brace. In the current test setup, the InMoov is elevated above the subject, removing vibrational cues. However, as a result of the previous experimental design and to facilitate the learning of the association of grasps to skin stretch stimuli, the skin stretch stimuli were presented on the right forearm. Other than the mirroring of the contact pads to place them on the right arm, the test setup is the same as for cluster sorting task in Chapter 3 and so, looks like the setup shown in Fig 1.2. As before, subjects listened to pink noise over headphones to block auditory cues.

In this task, subjects were passively presented with skin stretch stimuli representing grasps 4.1, transitioning from an open hand configuration (about 1.5N of initial tension) to the stimulus associated with a grasp over the course of 4 seconds. The amount of skin stretch per contact pad was proportional to each corresponding joint angle for each grip that the prosthetic hand performed. For example, for the thumb, index, and pistol grips, the thumb, index, and pistol contact pads would move a proportional amount as the grips completed. For the fine pinch, for instance, the contact pads for the thumb and index fingers would move through half of the range of their possible displacements since the thumb and index fingers only move through half of the possible range of their joint angles.

Subjects had an opportunity to learn the grasps and stimuli during two training periods where for each grasp, they were shown an image of the grasp, the associated skin stretch stimulus, and a view of the prosthesis as it
performed the grasp. Once the grip completed, it held for 3 seconds before releasing back to an open configuration to wait 2 seconds before the next grasp. For the first training period, each grasp was shown twice in random order. In the second period, each grasp was shown 3 times in random order, and subjects identified the associated grips within 3 seconds of completion. They were told the correct grasp after each identification. Total training time was 6 minutes. During the evaluation phase, subjects were presented with each grasp and associated skin stretch stimulus 5 times in random order for a total of 30 stimuli. For this phase, the InMoov arm and the contact pads were obscured from view. Subjects were not told the correct grasp and had no time limit. We recorded the actual and predicted grasps.

4.2 Perceptual Structure According to the Confusion Matrix

We used the actual and predicted grasps to create a confusion matrix (Fig. 4.2). Diagonal entries depict how often subjects were able to correctly identify a grasp and off-diagonal terms show how a grasp was misidentified. The most commonly confused grasps were power and pinch which were confused 18 out of 110 times either power or pinch were presented. The most confused grasps were pinch and power, power and tool, and pinch and tool, which are all the pairwise combinations of 3-DOF grasps. In general, subjects confused 3-DOF grips more often than single-DOF. In addition, they confused them more often with other 3-DOF grips.

To use the confusion matrix to help us determine the perceptual structure for the skin stretch device, we defined the accuracy in distinguishing between a pair of stimuli to be

\[ \text{Accuracy} = \frac{P - C}{P} \times 100, \]

where \( P \) is the total number of times either stimulus was presented (5 for stimulus \( i \) and 5 for stimulus \( j \) per subject for 11 subjects for a total of 110) and \( C \) is the number of times the stimuli were confused.

We also mapped the stimuli used during the Grip Recognition Task to a 3D perceptual space with the same dimensions found using MDS. That is,
each dimension was the displacement for one contact pad. We normalized
the displacement of the individual contact pads by the maximum possible
displacement, which was 13 mm. Each grasp then had an (x,y,z) coordinate
in the perceptual space determined by the normalized displacement of each
contact pad at the end of the grasp (Fig. 4.3). The Euclidean and Manhattan
distances were then calculated between each pair of stimuli. If we can
show that increasing Euclidean distances correspond to decreasing confusion
between grasps for more pairs of grasps than for increasing Manhattan
distances and if we can demonstrate that the Euclidean distance can be used
to predict the confusion matrix, then the distance metric for the perceptual
space for the skin stretch device is Euclidean. Then, the structure of the
perceptual space for multi-DOF linear skin stretch is integral by definition.

Table 4.1 lists the Euclidean 2-Norm distance between the skin stretch
stimuli for a pair of grasps in the perceptual space alongside the accuracy
computed from the confusion matrix. The general trend is that pairs of
grasps which have stimuli closer together in the perceptual space are confused
more often. The tool and pistol grasps are an exception to this trend. In
addition, we present Table 4.2, which lists the Manhattan distance rather
than Euclidean distance. Compared to the table with Euclidean distances,
more grasps fail to meet the trend that the further away stimuli are in a
perceptual space, the less confused they will be, suggesting that the Euclidean
distance is a better distance metric for the perceptual space for skin stretch
than the Manhattan distance.

Figure 4.4 shows the correlation between the Euclidean distance between
stimuli in the perceptual space and their accuracy. We found the best fit
logistic curve because in a perceptual space because the further stimuli are
apart, the easier they are to distinguish, but accuracy cannot exceed 100%.
As a result, like many other psychophysical studies, we use a logistic curve
[25, 46], and constrain it to an asymptote of 100% accuracy.

\[
Accuracy = \frac{100}{1 + e^{3.25(-X+0.05)}}
\]

where \(X\) is the distance between stimuli in the perceptual space. This fit
had \(R^2 = .90\), providing further evidence that the perceptual space has a
Euclidean distance metric and therefore, has an integral perceptual structure.
4.3 Discussion

We converted the skin stretch stimuli used during the Grip Recognition Task into points in the perceptual space by normalizing the displacement of each contact pad during a grasp by the maximum possible displacement, which implicitly established a scale for the perceptual space. Proceeding with the normalized scale, we found the distances between skin stretch stimuli in the normalized perceptual space, which were subsequently compared to the amount of confusion between associated grasps. There was a general trend that closer stimuli were confused more often. However, an interesting exception was the relatively low confusion between Pistol and Tool grips. This may be due to a nonlinear scaling in the perceptual dimension for the displacement of the thumb contact pad, which would increase the distance between the Pistol and Tool grips.

Overall, we found a strong logistic correlation between distance and accuracy ($R^2 = 0.90$). Of note is that at zero distance, the 45.6% accuracy is near 50% chance, which is what we would expect when two stimuli are perceptually indistinguishable. According to the logistic curve, stimuli in the perceptual space should be at least a distance of 0.96 normalized units apart to get at least 95% accuracy.

During our analysis, we normalized the physical dimensions of contact pad displacement to put the skin stretch stimuli into the perceptual space. This step may have been unnecessary as the consequent analysis would be similar if the absolute physical dimensions had been used instead. In order to establish whether the scale is normalized or absolute, further experiments would be necessary with different maximum possible displacements.
4.4 Figures

Figure 4.1: Grasps for Grip Recognition Task.

Figure 4.2: Confusion Matrix for Grip Recognition Task. The confusion matrix depicts what subjects predicted the grasp to be when provided with skin stretch stimuli representing the actual grip. The higher the values along the diagonal, the better subjects were at correctly identifying grasps. In general, subjects confused 3-DOF grips more often than single-DOF. In addition, they confused them more often with other 3-DOF grasps. The most confused grasps were pinch and power, power and tool, and pinch and tool, which are all the pairwise combinations of 3-DOF grasps.
Figure 4.3: Grasps and their trajectories through the perceptual space.
Figure 4.4: Logistic relationship between Euclidean distances in the perceptual space and classification accuracy. Blue represents confusion between pairs of 3-DOF grasps, red between pairs of single-DOF grasps, and purple between a 3 and single-DOF grasp. The legend is in order of distance and the shape of the marker has no inherent meaning. Power-Thumb and Thumb-Pistol are at the same location. Subjects appeared to have higher accuracy for pairs of stimuli which were farther apart in the perceptual space. A logistic fit constrained to an asymptote of 100% accuracy had an $R^2 = 0.90$. The 45.6% accuracy at zero distance is near 50% chance, which is expected when stimuli are indistinguishable.
4.5 Tables

Table 4.1: Ranked list of pairs of stimuli according to their Euclidean distance from each other in the perceptual space in ascending order. The number of times the stimuli were confused in the Grip Recognition Task is also included. Notice that other than one entry for Pistol-Tool, the Number of Times Confused increases monotonically with the Euclidean distance.

<table>
<thead>
<tr>
<th>Grasp A</th>
<th>Grasp B</th>
<th>2-Norm</th>
<th>Number of Times Confused</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pinch</td>
<td>Power</td>
<td>0.52</td>
<td>18</td>
</tr>
<tr>
<td>Power</td>
<td>Tool</td>
<td>0.71</td>
<td>14</td>
</tr>
<tr>
<td>Pinch</td>
<td>Tool</td>
<td>0.86</td>
<td>10</td>
</tr>
<tr>
<td>Pistol</td>
<td>Tool</td>
<td>0.96</td>
<td>2</td>
</tr>
<tr>
<td>Thumb</td>
<td>Pinch</td>
<td>0.99</td>
<td>6</td>
</tr>
<tr>
<td>Tool</td>
<td>Thumb</td>
<td>1.05</td>
<td>4</td>
</tr>
<tr>
<td>Pinch</td>
<td>Index</td>
<td>1.08</td>
<td>4</td>
</tr>
<tr>
<td>Pistol</td>
<td>Index</td>
<td>1.35</td>
<td>4</td>
</tr>
<tr>
<td>Power</td>
<td>Thumb</td>
<td>1.35</td>
<td>1</td>
</tr>
<tr>
<td>Thumb</td>
<td>Pistol</td>
<td>1.35</td>
<td>1</td>
</tr>
<tr>
<td>Power</td>
<td>Index</td>
<td>1.35</td>
<td>0</td>
</tr>
<tr>
<td>Thumb</td>
<td>Index</td>
<td>1.41</td>
<td>1</td>
</tr>
<tr>
<td>Power</td>
<td>Pistol</td>
<td>1.41</td>
<td>0</td>
</tr>
<tr>
<td>Pistol</td>
<td>Pinch</td>
<td>1.45</td>
<td>0</td>
</tr>
<tr>
<td>Tool</td>
<td>Index</td>
<td>1.52</td>
<td>0</td>
</tr>
</tbody>
</table>
Table 4.2: Ranked list of pairs of stimuli according to their Manhattan distance from each other in the perceptual space in ascending order. The number of times the stimuli were confused in the Grip Recognition Task is also included. Notice that Pistol-Tool, Thumb-Pinch, and Pinch-Tool prevent the Number of Times Confused from ascending monotonically with the Manhattan distance.

<table>
<thead>
<tr>
<th>Grasp A</th>
<th>Grasp B</th>
<th>Manhattan</th>
<th>Number of Times Confused</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pinch</td>
<td>Power</td>
<td>0.61</td>
<td>18</td>
</tr>
<tr>
<td>Power</td>
<td>Tool</td>
<td>0.88</td>
<td>14</td>
</tr>
<tr>
<td>Pistol</td>
<td>Tool</td>
<td>1.30</td>
<td>2</td>
</tr>
<tr>
<td>Thumb</td>
<td>Pinch</td>
<td>1.30</td>
<td>6</td>
</tr>
<tr>
<td>Pinch</td>
<td>Tool</td>
<td>1.31</td>
<td>10</td>
</tr>
<tr>
<td>Tool</td>
<td>Thumb</td>
<td>1.40</td>
<td>4</td>
</tr>
<tr>
<td>Pinch</td>
<td>Index</td>
<td>1.48</td>
<td>4</td>
</tr>
<tr>
<td>Pistol</td>
<td>Index</td>
<td>1.91</td>
<td>4</td>
</tr>
<tr>
<td>Power</td>
<td>Thumb</td>
<td>1.91</td>
<td>1</td>
</tr>
<tr>
<td>Thumb</td>
<td>Pistol</td>
<td>1.91</td>
<td>1</td>
</tr>
<tr>
<td>Power</td>
<td>Index</td>
<td>1.91</td>
<td>0</td>
</tr>
<tr>
<td>Thumb</td>
<td>Index</td>
<td>2.00</td>
<td>1</td>
</tr>
<tr>
<td>Power</td>
<td>Pistol</td>
<td>2.00</td>
<td>0</td>
</tr>
<tr>
<td>Pistol</td>
<td>Pinch</td>
<td>2.43</td>
<td>0</td>
</tr>
<tr>
<td>Tool</td>
<td>Index</td>
<td>2.60</td>
<td>0</td>
</tr>
</tbody>
</table>
CHAPTER 5
LINEAR SKIN STRETCH IN
PROPRIOCEPTIVE TARGETING TASKS

In addition to performing a perceptual analysis to show that linear skin stretch is suited to the task of providing proprioceptive feedback from a perceptual-cognitive point of view, we compared the passive, linear skin stretch device against no proprioceptive feedback and against a vibrotactile array. No proprioceptive feedback exists for commercial prostheses [47, 48], and a vibrotactile array is one of the best performing proposed sensory substitution methods for single-DOF proprioception [10]. [7] measured the performance of skin stretch, vibrotactile, and no feedback substitution for proprioception with one joint angle using a commonly performed single-DOF task [11]. Because the skin stretch device can extend to multi-DOF, we also compared skin stretch against no feedback in a multi-DOF Grip Aperture Targeting Task. For single-DOF proprioception, skin stretch and vibrotactile showed no significant difference in mean absolute joint angle error, but both were significantly better than when there was no feedback. For multi-DOF proprioception, skin stretch had significantly smaller aperture error than no feedback for grasps involving changes in multiple joint angles.

As a result, our skin stretch device can provide proprioception for a single-DOF at a level of performance similar to a vibrotactile array for single-DOF proprioception, and we have shown that it can be used to provide multi-DOF proprioception. However, the passive, linear skin stretch device has other benefits over a vibrotactile array because the skin stretch device requires less surface area on the skin per DOF [7] and is less annoying [49].

The work in this chapter was first presented in [7].
5.1 Experimental Setup for Targeting Tasks

Five unimpaired subjects, 4 male, 1 female (ages: 19-27), volunteered for two experiments, one testing single-DOF proprioception and the other testing multi-DOF proprioception. During each experiment, six electrodes were placed over the finger flexor and extensor muscle groups located radially around the right forearm, with three electrodes being placed over each muscle group. A 16-channel Delsys Bagnoli system (Delsys, Inc., Natick, MA) was used to record the EMG signals measured across these muscles. All data were collected and processed using the MATLAB DAQ Toolbox (Mathworks, Natick, MA).

5.2 Single-DOF Virtual Finger Task

In the first experiment, subjects were asked to move an on-screen virtual finger in a single-DOF task (Fig. 5.1a) based on [11] and [50]. The virtual finger was constrained to move between 0-90°. Meanwhile, the subject’s metacarpophalangeal (MCP) joints on the right hand were restrained to 45° in order to remove any of the subject’s own proprioceptive cues in controlling the arm. Flexing or extending the MCP joints against the restraint (Fig. 5.1b) would generate EMG signals. Linear discriminant analysis was used to classify these EMG signals to virtual finger movements every 0.1 s, following the procedure outlined in [51]. In order to have subjects rely more on feedback than timing-based open loop control strategies [52], the angular velocity was changed by a random walk bounded between 5-20°/s with a random initial velocity. Three feedback conditions were tested during the Virtual Finger Task: vibrotactile feedback, passive linear skin stretch feedback, and no feedback.

5.2.1 Experimental Setup

To provide passive skin stretch for proprioceptive substitution, we used the same modified InMoov arm shown in Ch. 1. For the targeting experiments of this chapter, we seated the hand in a rigid plastic interface, which was then attached to a wrist brace. Guide holes at the proximal end of the interface kept the lines to the contact pads as horizontal as possible to maximize shear.
forces on the skin. For the single-DOF task, we adhered only the contact pad for the index finger to the skin (Fig. 5.1c).

As a comparison to skin stretch for the single-dof virtual finger task, we used a vibrotactile array based on [52] to provide proprioceptive feedback of the angle of the virtual finger. It consisted of eight standard ERM motors placed longitudinally along the forearm, with each tactor spaced 29 mm apart (Fig. 5.1b). The joint angle range of the virtual finger was divided into eight intervals, each successively mapped to one of the vibrotactile motors.

5.2.2 Training and Evaluation

A trial consisted of a training and evaluation phase for a particular feedback condition. During training, each subject used EMG to freely control the virtual finger for 60 s. Next, the subject was given five practice target angles from the evaluation phase. They were asked to move the virtual finger, now invisible, until it matched a series of displayed targets (Fig. 5.1a). Once the subject believed he was at the target angle, he would press a button and would be shown the actual angle to which he moved. Following the five practice angles, the subject was evaluated using 20 more targets. We recorded the mean absolute error between the target angle and the subject’s estimate.

Subjects participated in two sessions consisting of a trial for each of the three feedback conditions, with each condition presented in a random order. Two sessions were conducted in order to evaluate whether performance improved over time. To help ensure subjects relied only on the feedback method under consideration, they wore headphones playing pink noise throughout the experiment. Additionally, when evaluating linear skin stretch, the prosthesis and contact pads were occluded from view.

5.2.3 Results and Discussion

The no feedback, vibrotactile, and skin stretch conditions had $(17.75 \pm 5.17^\circ)$, $(8.58 \pm 2.12^\circ)$, and $(9.79 \pm 2.68^\circ)$ of mean absolute error, respectively. We ran a two-way repeated measures ANOVA, where the within-subject factors were session number and feedback condition. We found a significant
difference between the no feedback and vibrotactile conditions ($p < 0.01$) as well as the no feedback and skin stretch conditions ($p < 0.05$) (Fig. 5.2). However, there were no significant differences between skin stretch and vibrotactile or between sessions for any feedback condition. In addition, users of prostheses have reported that vibrotactile feedback becomes distracting after prolonged periods of time [49], though constant proprioceptive feedback may be desired. Subjects in this study reported skin stretch remained comfortable throughout the experiments, which could make it more desirable than vibrotactile stimulation at providing proprioceptive feedback.

5.3 Grip Aperture Targeting Task

The Grip Aperture Targeting Task involved six grips plus a starting reference configuration (open hand) (Fig. 4.1), the same ones used by the Grip Recognition Task presented in Ch. 4. To examine whether single-DOF grips could be distinguished from multi-DOF grips, half of the grips chosen displaced a single contact pad: the thumb, index, and pistol grips. The other three grips displaced multiple contact pads simultaneously: power, fine pinch, and tool grips. The amount of skin stretch per contact pad was proportional to each corresponding joint angle for each grip. These specific multi-DOF grips were chosen because they are commonly implemented in upper limb myoelectric prostheses [8].

The purpose of this task was to extend the single-DOF virtual finger task to incorporate the six grips from the grip recognition task. The aperture of each grip was normalized from 0% (open hand) to 100% (completed grip). Subjects had to match target apertures at 25%, 50%, and 75% grip completion using EMG control.

To decouple EMG pattern recognition errors from the errors generated from matching a percent aperture for a grip using skin stretch or no feedback, the grips were pre-selected. Subjects flexed or extended the same muscles from the single-DOF task to control the aperture for all grips.
5.3.1 Experimental Setup

To extend the single-DOF skin stretch feedback to multi-DOF, we introduced two additional contact pads to either side of the right forearm. We placed a contact pad on the ulnar side for the middle finger, the middle for the index finger as before, and the radial side for the thumb (Fig. 5.1c). Subjects were evaluated with skin stretch and no feedback conditions. As before, subjects listened to pink noise through headphones and the prosthesis, and contact pads were hidden from view during evaluation.

5.3.2 Training and Evaluation

During training, the subject was prompted to close a grip to within ±5% of a target percent aperture and stay in the zone for 2 s. This was repeated for each of the six grips at each of the three target apertures, presented in a randomized order.

Evaluation consisted of 30 random targets in which the subject tried to match percent aperture after starting from a random percentage between 0-100%. In order to reduce the completion time of the experiment, a random subset of all the combinations of grip and percent aperture were presented to each subject. Subjects repeated the task twice for both no feedback and skin stretch feedback conditions, with the order of conditions randomized. The mean absolute error between the target percent and subject’s estimate was recorded.

5.3.3 Results and Discussion

Figure 5.3 shows that the error in percent aperture for the skin stretch condition (11.1 ± 1.5%) was significantly lower ($p < 0.05$) than the no feedback condition (18.7 ± 5.1%). We see that subjects performed better with skin stretch feedback than without, regardless of the grip.
5.4 Summary

By performing these targeting experiments, we have been able to compare the use of skin stretch to vibrotactile and no feedback substitution for proprioception for a myoelectric hand. We showed that skin stretch helps subjects achieve proprioceptive targets as well as vibrotactile, which is one of the best performing proposed methods to provide proprioceptive information during grasping [10]. As a result, from the perspective of other sensory substitution devices in the literature, linear skin stretch is a suitable alternative for providing single-DOF proprioceptive information and compared to vibrotactile, less annoying [49].

The skin stretch device also uses less skin surface area than vibrotactile per DOF, requires little power, and is lightweight [7]. Combined with subjects’ demonstrated ability to use the device to control the aperture of multi-DOF grasps, we see that single-DOF skin stretch can be easily extended to be used for multi-DOF proprioception.

As a result, we now have both perceptual-cognitive and comparative evidence that multi-DOF skin stretch can be used by subjects as a multi-DOF proprioceptive substitution device.
5.5 Figures

Figure 5.1: (a) MATLAB GUI used for the single-DOF virtual finger task. (b) Vibrotactile array placement. (c) Passive linear skin stretch setup for targeting tasks. A third contact pad was adhered to the skin on the radial side of the forearm. The orange triangular block restrained the subject’s hand in order to remove intrinsic proprioceptive cues.

Figure 5.2: Average mean absolute error for the single-DOF virtual finger task. There was no significant difference between skin stretch and vibrotactile feedback but having either skin stretch ($p < 0.05$) or vibrotactile ($p < 0.01$) feedback performed significantly better than without.
Figure 5.3: Average percent grip aperture error for the grip aperture targeting task. There was a significant difference in error ($p < 0.05$) between using skin stretch and not having feedback to match a grip aperture.
6.1 Future Work

Future work will involve verifying that adding more contact pads to provide proprioception for more fingers will maintain the matched dimensionality and structure between the task and the perceptual space of the passive, linear skin stretch device. In addition, while we worked with normalized units for the perceptual space, it is possible that the space actually depends on absolute units, which we can test by analyzing the confusion matrix for an identification task where the contact pads displace the skin by a reduced amount. Based on [25], it is expected that dimensionality and structure will match for more joint angles and that whether normalization is necessary depends on the number of skin stretch stimuli and associated grasps subjects need to identify. Armed with this knowledge, it could be possible to predict the confusion matrix for skin stretch stimuli representing a larger set of grasps, which require knowledge about the joint angles for all five fingers. In addition, it may now be possible to design the trajectories of skin stretch stimuli through the perceptual space so that users will know which grasp they are performing without having to close their hand as far. A possible approach is to increase the distance between the trajectories for different grasps at the beginning of the trajectory when the hand is beginning to close.

6.2 Summary

In this thesis, we performed a perceptual analysis and a set of single and multi-DOF targeting tasks to determine the suitability of a 3-DOF passive, linear skin stretch device for 3-DOF proprioception. During the perceptual
analysis, we found that both the dimensionality and structure of the task and the perceptual space for the device match, providing perceptual-cognitive evidence that passive, linear multi-DOF skin stretch can be used to provide sensory substitution for multi-DOF proprioception. We also performed a targeting task to see if linear skin stretch would be a viable alternative to a vibrotactile array, which has been proposed as a sensory substitution device in the literature [10, 12]. We found that subjects showed no significant difference in their ability to reach a target joint angle when using the skin stretch device or a vibrotactile array. For both the single and multi-DOF targeting tasks, skin stretch performed significantly better than when there was no feedback. The results of our perceptual analysis and targeting task offer strong evidence that multi-DOF linear skin stretch can be used as a sensory substitute for multi-DOF proprioception.
REFERENCES


