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An evaluation of clustering techniques to classify dexterous manipulation of individuals with and without dysfunction*

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***Abstract*—The rehabilitation of manipulation ability in orthopedic (e.g., thumb carpometacarpal osteoarthritis- CMC OA) and neurological (e.g., Parkinson's disease- PD) conditions depends critically on our ability to detect dysfunction and quantify its evolution and response to treatment. The Strength-Dexterity (SD) test is a validated indicator of dynamic dexterous manipulation function, but its ability to categorize clinical populations has not been tested. We 1) used the SD test to compare manipulation ability among patients with OA and PD and healthy age-matched elderly control subjects; and 2) compared and evaluated the ability of different clustering techniques to classify subjects into clinical or control groups and calculate their respective cluster centroids. We considered five clustering methods (three hard and two fuzzy): K-means, K-medoids, Gaussian expectation-maximization (GEM), Subtractive, and Fuzzy C-means clustering. We found the centroids of the SD test scores differed significantly between the clinical and control groups. Of the five methods considered, the GEM clustering algorithm most accurately classified SD test performance between these two groups.**

I. INTRODUCTION

Numerous conditions impair sensorimotor function of the hand, including osteoarthritis (OA) and Parkinson's disease (PD). OA is the most common form of arthritis and is a major cause of pain and disability in the elderly affecting millions of people in the United States alone [1, 2]. The reduced functional ability associated with OA reported by both clinicians and patients can be attributed to mechanical properties, such as joint pain and stiffness, however other factors are also likely to contribute [3, 4]. OA related sensorimotor deficiencies include impaired proprioception [2, 5, 6], muscle weakness and fatigue [3], and unequal muscle activation patterns [3-5], and a reduction in gray matter due to pain [7]. PD is a progressive neurological disorder, most commonly associated with the elderly, characterized by numerous motor features including tremor, rigidity, bradykinesia, and postural instability, which can impact sensorimotor function to varying degrees [8, 9]. The loss of manual dexterity frequently occurs in people diagnosed with PD and CMC OA, and can affect performance of activities of daily living (ADLs) including writing, cutting food and feeding, and dressing [1, 2, 8, 9]. While it is known that dysfunction of the musculature of the hand contributes to the reduction in function and ability to perform ADLs reported by and observed in individuals with CMC OA and PD, its extent remains unknown. Therefore, further research into understanding factors related to manipulation dysfunction might prove to be important in the clinical management of such individuals and in the evaluation of alternative treatments.

The Strength-Dexterity (SD) test is a validated instrument for quantifying dynamic dexterous manipulation at very low force levels < 3 N (300 gmf) [10-12], which when combined with cluster analysis may serve as a means to detect and quantify sensorimotor dysfunction during dexterous manipulation. The SD test involves using the fingertips to compress, as far as possible, a slender spring prone to buckling. This requires control of fingertip motions and force vectors at very low force levels [10-12]. Measuring dynamical ability with such low forces make it uniquely applicable to weaker clinical populations, children, and older adults. A lengthier version of the SD test has been shown to discern between older adults with and without CMC OA [10] and to quantify the development and decline of hand dexterity across the lifespan [13]. Further evidence suggests that the SD test quantifies a unique construct (i.e. dexterity) that is reflective of sensorimotor processing for skilled finger function because it is independent of strength [10-13], is affected by development and aging [13], and engages distinct cortico-striatal-cerebellar networks in a context-sensitive way [14]. We now 1) evaluate the ability of a shortened, clinical version of the SD test [12] to quantify differences in dexterous manipulation between older adults with and without hand dysfunction (due to CMC OA or PD) and healthy control subjects; and 2) compare and evaluate the ability of different clustering techniques to classify subjects into clinical or control groups and calculate their respective cluster centroids.

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II. METHODS

Cluster analysis is a method of grouping a set of objects in such a way that objects in the same group are more similar to each other than to those in other groups. We review five of the most representative off-line clustering techniques in this study to classify sensorimotor control of the hand as measured by SD test performance:

- K-means,
- K-medoids,
- Gaussian expectation-maximization (GEM),
- Subtractive, and
- Fuzzy C-means (FCM).

A. Training Data Set

The clinical group, defined as individuals diagnosed with either CMC OA or PD, consisted of 47 participants (37F, 10M, 66.4 ± 9.2 years, 69 hands). The control group consisted of 29 healthy, age-matched volunteers (19F, 10M, 65.6 ± 9.7 years, 52 hands) with no history of hand injury or disease or neurological disorder. All participants performed the SD test, which was conducted with a custom spring (Century Springs Corp., Los Angeles, CA) outfitted with two compression miniature load cells (ELB4-10, Measurement Specialties, Hampton, VA). The load cells were connected to a signal conditioning box and a USB-DAQ (National Instruments, Austin, TX) and sampled at 400 Hz using custom Matlab software (The Mathworks, Natick, MA) [12].

Participants were asked to compress the spring to the point of maximal instability they could sustain (i.e., beyond which they felt it would slip out of their hand), and maintain that level of compression at a steady level for at least three seconds [11, 12]. At least three successful compression holds were collected per subject. The dependent variables were the mean compression force (F), the mean first derivative of force ($\Delta F/\Delta t$), and the mean root-mean-square error (RMSE) of the maximal three hold phases. These data were considered the training data set for the second purpose of the study.

B. Clustering Techniques

We describe the five clustering algorithms briefly and provide references for further details. All techniques were applied to the data set in Matlab. Hard clustering techniques included in this study are either centroid-based (K-means and K-medoids) or distribution-based (GEM) algorithms. In fuzzy (or soft) clustering, each data point has a degree of belonging to clusters, rather than belonging completely to just one cluster as in hard clustering. As such, points on the edge of a cluster, may be in the cluster to a lesser degree than points in the center of cluster [15]. Fuzzy clustering techniques included in this study are Subtractive and FCM.

Hard clustering attempts to group a set of n vectors $\boldsymbol{x_j}$, $j = 1,\ldots, n$, into c clusters G_i, $i = 1,\ldots, c$. The first two techniques considered in this study, K-means and K-medoids clustering, are common centroid-based methods based on distance between an observation, $\boldsymbol{x_k}$, in group j and the cluster centroid, $\boldsymbol{c_i}$, are used to define the objective function given by (1) [16],

$$J = \sum_{i=1}^{c}\left(\sum_{k,x_c\in G_i}^{c} ||x_k - c_i||^2\right). \quad (1)$$

Once the cluster centers, c_i, are defined, the membership function, u_{ij}, groups an observation, $\boldsymbol{x_j}$, in the cluster with the nearest centroid and is defined by (2) [16],

$$u_{ij} = \begin{cases} 1\ if\ ||x_j - c_i||^2 \leq ||x_j - c_k||^2,\ for\ each\ k \neq\ i \\ 0,\ otherwise \end{cases}. \quad (2)$$

Both the K-means and K-medoids algorithms are partitional and both attempt to minimize squared error. However, unlike the K-means algorithm, the K-medoids technique specifies that centroids must be observations in that cluster.

In distribution-based clustering, clusters are defined as objects belonging most likely to the same distribution. An advantage is that it closely resembles the way artificial data sets are generated by sampling random objects from a distribution [17]. The third technique, GEM, is the most well known method of Gaussian-based clustering. The GEM technique alternates between performing an expectation (E) step, which creates a function for the expectation of the log-likelihood and a maximization (M) step, which computes parameters maximizing the expected log-likelihood found on the E step. This alteration continues between the two steps until the resulting values converge to fixed points. The objective function is given by (3) [16],

$$J = -\sum_{i=1}^{n} log\left(\sum_{j=1}^{c} p(x_j|c_i)p(c_i)\right), \quad (3)$$

where $p(x_j|c_i)$ is the probability that $\boldsymbol{x_j}$ is generated by the Gaussian distribution with center $\boldsymbol{c_i}$, and $p(c_i)$ is the prior probability of $\boldsymbol{c_i}$. The membership function, u_{ij}, is given by (4) [17],

$$u_{ij} = \frac{p(x_j|c_i)p(c_i)}{p(x_j)}. \quad (4)$$

GEM not only generates clusters, but also produces complex models for the clusters that can capture correlation and dependence of attributes, which can be informative.

The fourth technique, Subtractive clustering, is a fast, quick one-pass fuzzy algorithm for estimating the number of clusters and the cluster centers in a set of data based on density distributions [18]. Data points with high-density values have numerous neighboring data points and the points having the largest density values are designated cluster centers. The cluster density, D_j, at a given observation, $\boldsymbol{x_j}$, is calculated by (5) [18],

$$D_j = \sum_{i=1}^{n} exp\left(-\frac{||x_j - x_i||^2}{(r_a/2)^2}\right), \quad (5)$$

where r_a is a positive constant representing a neighborhood radius and x_i is the cluster center.

The fifth technique, FCM, follows the basic idea of K-means clustering with the difference that in FCM each data point belongs to a cluster to a degree of membership grade between 0 and 1, while in K-means every data point belongs to a cluster [19]. The objective function follows (1) and is given by (6) [19],

$$J(U, c_1, \ldots, c_c) = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m d_{ij}^2 , \qquad (6)$$

where u_{ij} is the membership value (between 0 and 1), $\boldsymbol{c_i}$ is the cluster center of the fuzzy group, d_{ij} is the distance between the cluster center and data point, and m is a weighting exponent [19].

III. Results

A. Sensorimotor Dysfunction as Measured by the SD test

The SD test provides the average compression force during the hold phases for each participant during the SD test, F, from which its maximal time derivative (ΔF/Δt) and root-mean-squared error (RMSE) are also obtained. We found no significant differences in average compression force, F ($p = 0.19$). However, two-tailed t-tests revealed that both mean ΔF/Δt ($p < 0.00001$) and mean RMSE ($p < 0.00001$) of the force signal during the hold phases of control participants were significantly lower than in individuals in the clinical group, indicating that control subjects display more efficient sensorimotor control of the hand (Table I).

The mean RMSE (abscissa) and mean ΔF/Δt (ordinate) for the control (red) and clinical (blue) groups were plotted and used as the training data set for the clustering analyses presented below (Fig. 1a).

B. Comparison of Clustering Techniques

The most appropriate clustering algorithm for a particular data set often needs to be chosen experimentally with a training data set. In this case, we applied three hard clustering algorithms, K-means, K-medoids, and GEM, to the data set described in the Methods section to determine the ability of each to correctly assign each observation to the appropriate group. The assigned groups from each method are illustrated in Fig. 1(b, c, d). GEM clustering was the most accurate clustering method (86% accuracy) followed K-means (81% accuracy) and then K-medoids (69% accuracy).

In addition to classification accuracy, we compared each clustering technique's ability to locate the centers of the two clusters. A cluster center indicates the heart of each cluster, so that when presented with an input vector, the system can determine which cluster to assign the input vector by measuring a similarity metric between the input vector and the cluster centers. The cluster centers for each group were calculated with the five algorithms and are presented in Table II along with the percent difference from the original centroids (Table I) for comparison purposes.

Table I: Dependent Variables from the SD test

Group	SD test dynamics (* p < 0.0001)		
	mean F (g)	*mean RMSE **	*mean ΔF/Δt **
Control	168.8±38.4	0.0673 *[C1x]*	0.0236 *[C1y]*
Clinical	174.8±41.1 (OA: 181.6; PD: 164.3)	0.1325 *[C2x]*	0.1212 *[C2y]*

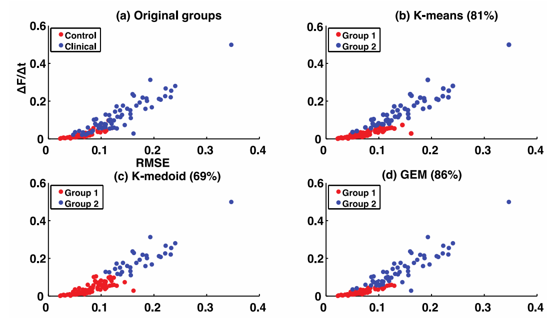

Fig. 1: Comparison of hard clustering techniques. The original data sets from the control and clinical groups are shown (a) and compared to groups created from K-means (b), K-medoids (c), and GEM (d) clustering, i.e. the three hard algorithms. Subtractive and FCM techniques are not illustrated, as they do not feature distinct cluster assignments.

Table II: Comparison of centroid locations by clustering technique

Cluster Method	Centroid Calculations				
	C1x	*C1y*	*C2x*	*C2y*	*% diff*
K-means	0.0779	0.0311	0.1668	0.1759	29
K-medoids	0.0819	0.0367	0.1729	0.1927	42
GEM	0.0701	0.0250	0.1381	0.1324	6
Subtractive	0.0756	0.0317	0.1395	0.1276	14
FCM	0.0793	0.0392	0.1833	0.2046	48

Centroids calculated by GEM clustering were the most similar to the original centroids (Table I) (6% difference), followed by Subtractive (14% difference), K-means (29% difference), K-medoids (42% difference), and FCM (48% difference). The original and estimated centroid locations for each group are further illustrated in Fig. 2.

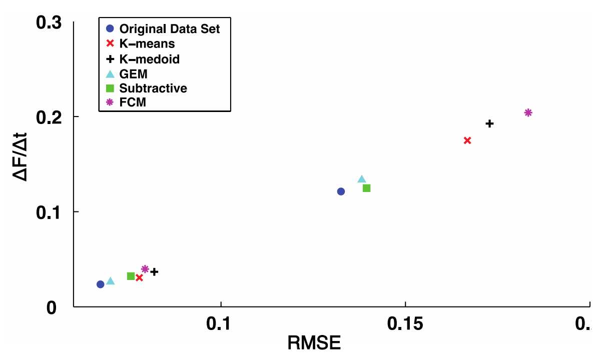

Fig. 2: Comparison of estimated centroid locations vs. original (true) locations.

IV. Conclusions

A key finding of this study is that, while clinical experience shows that CMC OA—a strictly skeletal condition—leads to loss of manipulation ability, it is surprising that its associated disability in manipulation is so similar to that found in PD—a strictly neurological condition. We find both clinical conditions are associated with significantly worse sensorimotor control of dynamic dexterous manipulation at very low force levels, which is critical to ADLs. This lends renewed urgency to better understand how degradation of the articular surface, a skeletal deficit, triggers a cascade of neuromuscular effects. That is, the functional link between skeletal and neuromuscular pathology is strong, but its mechanisms remain unclear. Note that for the purposes of this first comparison of clinical and control populations we grouped the patients with CMC OA and PD together. However, further work is needed to test for similarities and differences in the sensorimotor control deficits between CMA OA and PD, which are beyond the scope of this short paper. In addition, we find that the metrics obtained from the fast and simple SD test at low force magnitudes (which do not exacerbate joint tenderness or pain) are informative of the integrity of the neuro-musculo-skeletal system; and that clustering algorithms succeed with such data.

Clustering techniques have many applications including biological sciences data classification, character recognition, and astronomical classification [16]. We considered both hard and fuzzy clustering methods in this preliminary study. Fuzzy methods are often considered when sharp boundaries do not exist between data sets, as is the case in many real/biological applications. Three hard clustering algorithms (K-means, K-medoids, and GEM) were applied to the training data set to determine the ability of each to correctly classify data points into the clinical and control groups (Figs. 1(b,c,d)). GEM was the most accurate hard clustering method, correctly classifying 86% of the data points in the set. All five algorithms were used to estimate the centroids of the two clusters and the results are presented in Table II and illustrated in Fig. 2. Again, GEM clustering was the most accurate method for this data set, with estimated centroids 6% different from the original centroids.

While the GEM algorithm most accurately grouped the data set into the correct clusters, the accuracy of all methods was lower than desired at classifying data points at the cluster borders and estimating centroid locations, particularly for the clinical group (Fig. 2). Future work will consider more distribution-based clustering techniques in an attempt to improve the accuracy. These results show that borderline cases are naturally harder to classify, but the clear spread of the clinical group up and to the right (and the success at classification) shows that the SD test has potential to quantify the level of disability and response to treatment in non-borderline cases. We emphasize the need for future studies to identify and quantify sensorimotor changes in each of the pathologies studied, and the mechanism via which the SD test is able to detect those changes. Understanding the combined mechanical and sensorimotor effects of aging with a disability on quality of life and ability to perform ADLs is an important public health issue, and the SD test combined with a distribution-based clustering algorithm may be important tools to best develop and apply treatments to improve sensorimotor function for dexterous manipulation in our aging populations.

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