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Learning-based estimation of functional workspace in cooperative fingers motion

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Abstract. In hand therapy, it is essential to evaluate the cooperation of hand manipulations for the necessity of comprehending hand recovery. In this paper, we advocate a new computational method to estimate the functional workspace (FW) for quantifying the cooperative motion of thumb and finger, according to measurable motion trajectories only. This paper focuses on detailed implementation, some improvements and the synthetic validation works rather than the accompanied study in clinic [1]. The proposed estimation consists of the data regularizations, the parameterization of both the motion workspace (MW) of the thumb and finger's motion surface (MS), and the identification of finger's MS related to the parametric functions of thumb's MW by using a supervised learning approach. As a result, this method produces a low estimation error of FW/MW ratio (less than 5%) for the synthetic validation. Specifically, the estimation obtains reliable results for clinical trials, most of which are consistent with the expected evaluation of hand rehabilitation.

Keywords: functional motion workspace, thumb-finger cooperation, data regularization

1. Introduction

Based on a computer-aided motion analysis system, the spatial and temporal representation of active fingers' motion plays is crucial to provide therapists with more worthwhile viewpoints of evaluation, such as relating to instantaneous joint deficiency movement or abnormal motion velocity in functional action [2]. Recent studies have begun to investigate associative terms such as the kinetic functions or kinematics features related to the measured MWs [3]. Although many studies focus on single-finger functions, the importance of the multiple-finger cooperative functions (e.g., grasping or pinching movements) is increasingly emphasized [4]. In this paper, we present a method to estimate the cooperative-motion functional workspace (FW), a specific MW known as the intersection area where the fingers and thumb probably interact. The maximum intersection area between a specific finger's motion surface (MS for full-extension to full-flexion) and the thumb's volumetric MW (maximum circumduction) is proposed to represent an evaluation of the fingers' cooperation, as shown in Fig. 1. Our new approach for FW estimation effectively tackles the difficulties produced by noisy measurements and irregular motion trajectories. It also successfully parameterizes the finger's MS and the boundary of the thumb's MW, and then estimates the FW, based on a learning strategy. As a result, the proposed method produced satisfactory results in clinical experiments, and has proved effective for further applications. Likewise, our accompanying paper investigated other clinical normal or patient data with estimated FWs to demonstrate the good capacity of this method for clinical evaluations [1].

2. Methods

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2.1. Adaptive resampling for data regularization

The captured finger motion data usually unevenly distributed. The proposed adaptive resampling method aims to tackle the densely sampled data (called the repeated measurements, the data points inside a small region) in very-low motion and the sparse distributed data in quick motion.

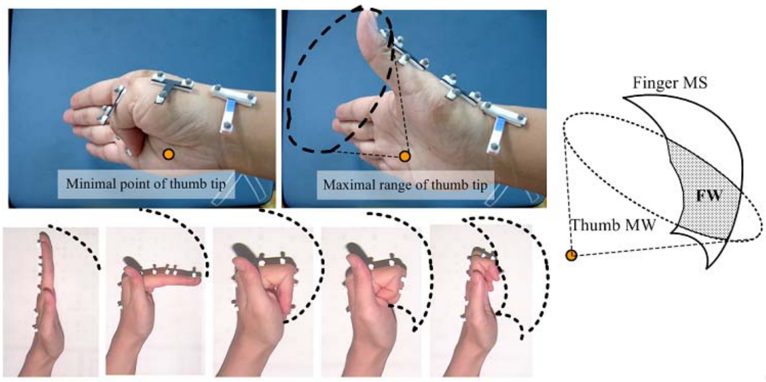

Fig. 1: UP: the pictures of thumb motion. Bottom: the five extreme actions of the flexion/extension of four fingers. Right: The indicating diagram for the functional workspace of the thumb and a specific finger.

In order to reduce the redundancy of repeated-measurement data with preserving the generality of motion trajectory, the proposed method samples the representative points of them only. Firstly, the repeated measurement value (RM) is adopted, which is defined as the frequency of appearing points within a circle with a given radius (called bandwidth value, BW). Then, we determine these thresholds based on the statistics of measured data points. In common, for densely repeated measurements, using a large bit BW and a small RM would lead to smoother trajectory by removing more unevenly distributed points. On the other hand, the sparse measurements, meant of having large distances between measured points and having zero RMs, are produced by quick motion and make the motion analysis less accurate. Thus, the policy of resampling is recommended to record additionally the padded data points by considering the coherence of the sparse measurement and its neighbouring data points. The padded data points are generated by interpolations with the cubic spline algorithm to reconstruct the lost information. As a result, the measured data points are regularly resampled (see Fig.3 (b)). In addition, for much noisier data from patients, this method can also be implemented with hierarchical structure to obtain sufficiently smooth results.

2.2. Meshing the finger's motion surface

After data regularization, we then propose to parameterize motion workspaces in geometry for FW estimation. The parameterization of finger's MS is a problem of parametric surface representation. A general 3D surface can be represented by using numerous piecewise meshes which are the planar patches generated as polygons [5]. Here, the fully automated meshing algorithm is applied, and the finger's MS can be parameterized by un-overlapped meshes (i.e., the 3D coordinates of polygon's vertices are seen as parameters). Meshing finger's MS only based on motion contour is difficult for it reveals a warping surface. Here, we propose a flexible meshing algorithm specifically for fingers' MS in principle of preserving well-form meshes by rectifying polygon's vertices.

The MS meshing is addressed based on the observation in physiology and kinesiology researches [6]. That claims the contour of finger's flexion/extension is close to coplanar and consists of two separated paths, which are divided by a given cut point (middle point) and called the forward (full-extension to full-flexion) and backward (full-flexion to full-extension) paths respectively, as shown in Fig.2 (a). Next, the piecewise meshes of MS can be defined by linking lines between the corresponding points on the forward and backward paths. With enough points sampled from the two paths (to make the finer level-of-detail) and eliminating too-thin meshes by adjusting vertices, the flexibility of the proposed meshing method can tackle the warping surfaces and construct the MS which reveals well approximating to real motion surface.

2.3. Parameterization of thumb's motion workspace

The next stage is for the parameterization of thumb's MW. As mentioned above, adopting a volumetric cone to parameterize thumb's MW makes some previous models ineffective for patients' motions [3].

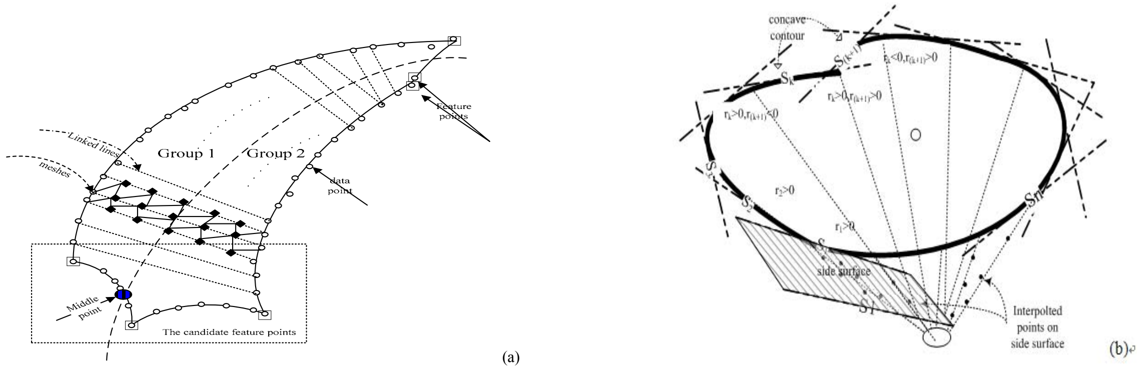

Fig. 2: (a) Illustrations of the middle point, linked lines and polygons for determining the motion surface (MS) of a specific finger. (b) The multiple fitting surfaces and the identification vectors of the boundary.

Differently, by utilizing multiple surfaces, the proposed method makes a higher flexibility to parameterize thumbs' MWs more effectively. The upper surface denoted $\hat{S}^{upper}_{thumb}$ is adopted to envelop the extreme thumb-tip points. It is formulated by second-order function, as denoted in (1), and can be estimated optimally by using the k resampled points ($\hat{p}^{thumb}_{j}$) of thumb-tip positions in circumduction with satisfying the following criteria in (2).

$$f(a,b,c,d) = ax^2 + bxy + cy^2 + d - z = 0\,, \tag{1}$$

$$\hat{S}^{upper}_{thumb}(a,b,c,d) = \underset{a,b,c,d}{\arg\min} \left\| f(a,b,c,d) - \hat{p}^{thumb}_{j} \right\|, j = 1....k\,, \tag{2}$$

The problem of optimization can be solved by a pseudo-inverse matrix calculated under the Maximum-Likelihood (ML) criteria directly. Furthermore, the side boundary of thumb's MW can be determined based on the maximum circumduction contour and the lowest-position point of thumb motion (the orange point in Fig.1). As shown in Fig. 2 (b), using multiple fitting surfaces (denoted $S_1, S_2....S_n$) makes a success in parameterization of thumb's MW including the concave-shape parts of boundary. This approach directly divides the side boundary into many piecewise convex parts, and then each part is fitted by a specific side surface. The interpolated auxiliary points (i.e., $ip^{thumb}_{h}, h = 1...n$) on side surface are assigned belonging to some convex part and adopted to construct the associated side surface ($\hat{S}^{thumb\_side}_{h}$, $h = 1...n$), using first-order functions by optimization. Note that the n is selected according to the irregular level of thumb's MW (i.e., about 8 to 12 here).

2.4. Estimating functional workspaces (FW) by supervised learning

In fact, the FW is composed of the polygons on finger's MS, which locate inside the thumb's MW. Thus, the location of polygons must be identified. And it can be carried out by employing the parametric fitting surfaces of thumb's MW. In mathematical representation, the sign of function value can indicate which geometric region the point belongs to. Therefore, regarding to the thumb's MW region which is enveloped by multiple fitting surfaces, the point locating in this region may produce a sign sequence of function values with respect to their fitting surfaces. In other words, this sign sequence can be used to identify the locations of the points of the finger's MS polygons.

As the motion of the thumb may not be a perfect convex shape, the thumb's MW consists of several geometric regions which have different sign sequences. All these sequences are acceptable for identifying whether the corresponding point is inside the thumb's MW or not. Thus, a point is regarded as inside the 3D space of the thumb's MW if its sign sequence is one of the acceptable sequences. For a polygon on the finger's MS, each vertex point can produce a sign sequence which is recorded by a (n+1)-dimensional vector of signs corresponding to totally (n+1) fitting surfaces, called the identification vector ($\vec{R}$) in (3).

$$\vec{R}\,(\cdot) = \left\langle sign(\hat{S}^{thumb\_side}_{1}), sign(\hat{S}^{thumb\_side}_{2})......, sign(\hat{S}^{thumb\_side}_{n}), sign(\hat{S}^{upper}_{thumb}) \right\rangle \tag{3}$$

The identification vector ($\vec{R}$) can then be used to identify the location of each vertex point. Then, all possible identification vectors inside the thumb's MW are included in a set called the acceptable set ($\{\vec{R}^h_{valid}\}_{h=1...n}$). The identification vectors in the acceptable set can be trained by using a large number of randomly selected points widely scattered in the thumb's MW. Therefore, each polygon (p) could be classified into three cases: (1) the polygon is completely inner (labelled 'in'), (2) completely outer (labelled 'out') or (3) across (labelled 'cross') the boundary of thumb's MW. (i.e., in, cross and out), according to the three identification vectors of vertices by the following criteria.

$$in \quad : if \quad \frac{\sum_{i=1}^{3} Max(\langle \vec{R}_i \cdot \vec{R}_{valid} \rangle)}{\sum i} \geq (n+1) \tag{1}$$

$$corss \quad : \quad n < \frac{\sum_{i=1}^{3} Max(\langle \vec{R}_i \cdot \vec{R}_{valid} \rangle)}{\sum i} < (n+1) \tag{2}$$

$$out \quad : \quad \frac{\sum_{i=1}^{3} Max(\langle \vec{R}_i \cdot \vec{R}_{valid} \rangle)}{\sum i} \leq n \tag{3}$$

Furthermore, the FW is included in the space composed of the polygons labeled as 'in' and 'cross'. As the cross-labeled polygon intersects the thumb's MW, the polygon's region inside the thumb's MW should be calculated in detail based on the intersected boundary of MW. Finally, the area of FW can be obtained by summarizing the total estimated areas from both 'in' labelled polygons (with area A_{in}) and 'cross' labelled polygons (with area A_{cross}). Then the ratio of cooperation area related to the entire area of finger's MS, called the normalized FW/MW ratio (R_{FCW}) as:

$$R_{FCW} = (A_{cross} + A_{in}) / A_{total} . \tag{4}$$

This ratio represents the functional proportion of finger motion in clinical evaluations.

3. Experiments and Results

The experiments demonstrated the efficiency and accuracy of the proposed method in clinical data. Five well-trained subjects participated with no history of hand injuries or diseases in the experiments. The results have been listed in Table 1 and the FW of subject 2 has been illustrated in Fig.3 (b). As the Table 1 shows, it is a worthy concern that the index finger has the largest average FW/MW ratio of 26.77%, with an FW area of 1159.3 mm^2. However, interestingly, the middle finger which had the largest motion area has the second largest FW ratio of 21.86%, with an FW area of 1353.7 mm2. This evidence supports the viewpoint that the index finger is more important than the middle finger for cooperative functions in hand therapy.

4. Conclusion

In this paper, we provide a new approach to estimate the cooperative workspace of the thumb and fingers. This method provides an adaptive approach to cope with noisy measured motion data, including repeated and sparse measurements. Moreover, the proposed method adopts multiple fitting surfaces to more precisely parameterize the thumb's MW, contrary to those adopted by conventional strategies. Furthermore, the piecewise-planar meshing for the finger's MS and the learning-based polygon identification are also provided as an aid to achieving a successful FW estimation. Consequently, the proposed method produces satisfactory resampling and fitting errors, which make this method more reliable. In addition, the resultant order of the FW/MW ratios associated with four fingers is consistent with the general expectations in the clinical evaluation of hand rehabilitation.

Although the FWs are successfully estimated to aid our understanding about cooperative motion to a remarkable extent, the FW/MW ratios only provide indicative information for hand therapy. However, they also lack complete analyses regarding the joint configurations in functional cooperative motion. Thus, further studies intend to investigate the feasible range of finger joints, over which the finger is able to interact with the thumb in cooperative motion. Besides, determining the time-varying configurations of the cooperative fingers is also worth investigating.

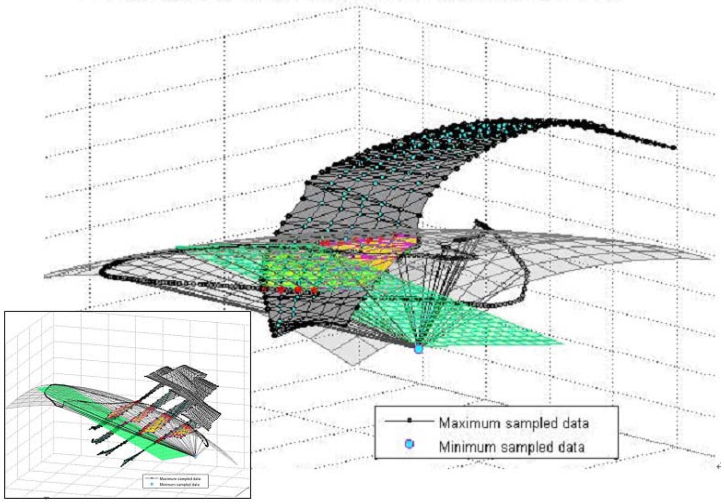

Fig. 3: The resampled points for reconstructing functional workspace (FW) of two objects The FW of the index and thumb. The left small diagram shows all the FWs of the thumb and the four digits.

Table 1: The area and ratio of Functional Workspace, the identification data for the thumb's MW

	Index		Middle		Ring		Little	
	FW area	FW/MW	FW area	FW/MW	FW area	FW/MW	FW area	FW/MW
Subject1	1857.39	35.61±3.4%	1914.01	24.32±2.7%	1546.08	19.25±1.4%	367.14	8.68±5.5%
Subject2	1256.34	36.65±3.1%	1400.61	29.04±6.6%	677.75	18.8±10.8%	245.36	15.8±10.2%
Subject3	966.48	22.12±6.4%	1215.46	22.04±8.0%	1282.02	25.89±5.3%	368.26	20.93±10%
Subject4	685.06	22.27±5.3%	920.75	19.3±10.7%	668.22	14.53±3.3%	124.59	4.06±6.5%
Subject5	1175.16	28.38±6.1%	1622.22	21.22±5.5%	1055.29	14.40±9.8%	280.94	9.80±8.1%
Average	1159.28	26.77%	1353.73	21.86%	986.657	16.90%	326.852	12.27%
std	352.044	7.142%	471.39	6.907%	542.96	8.258%	100.86	6.5%

5. Acknowledgements

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6. References

[1] L.C. Kuo, H.Y. Chiu, C.W. Chang, H.Y. Hsu, Y.N. Sun. Functional workspace for precision manipulation between Thumb and fingers in normal hands. *J. Electromyography and Kinesiology*. 2009, **19**:829-839.

[2] H.Y. Chiu, S.C. Lin, F.C. Su, S.T. Wang, H.Y. Hsu. The use of the motion analysis system for evaluation of loss of movement in the finger. *J. Hand Surgery*. 2000, British **25**: 195-199.

[3] L.C. Kuo, W.P. Cooney, K.R. Kaufman, Q.S. Chen, F.C. Su, K.N. An A quantitative method to measure maximal workspace of the trapeziometacarpal joint--normal model development. *J. Orthopedic Research*. 2004, **22**: 600-606.

[4] Z. Li, J. Tang. Coordination of thumb joints during opposition. *J. Biomechanics*. 2007, **40**: 502-510.

[5] M.S. Floater, K. Hormann. *Surface Parameterization: a Tutorial and Survey, Advances in multiresolution for geometric modeling*. Springer, 2005.

[6] A. Gupta, G.S. Rash, N.N. Somia, M.P. Wachowiak, J. Jones. The motion path of the digit. *Journal of Hand Surgery*. 1998: 1038-1042.