Geometrical model of muscle attachment sites in hand

T. Zítka[a], L. Havelková[a], R. Tupý[c]

[a] *Man-Machine Interaction department, New Technologies – Research Center, University of West Bohemia, Univerzitní 8, 306 14 Plzeň, Czech Republic*
[c] *Department of Imaging Methods, Medical School and Teaching Hospital Pilsen, Charles University in Prague, Pilsen, Czech Republic*

In biomechanical modeling acquiring appropriate data is a difficult task. In our study, we attempt to overcome this by using data from MRI. We obtained MRI scans of hand in which muscle attachment sites are identifiable. These allow us to create triangular meshes that accurately model muscle origin and insertion surfaces. In AnyBody Modeling System individual muscles are replaced with user defined number of action lines or virtual muscle elements. These elements need to be placed within muscle volume in a way that respects anatomy of the muscle. This breaks into two tasks: placing required number of endpoints onto attachment surfaces and then pairing these endpoints in order to specify individual elements.

For the first task we use modified k-means algorithm. Given a finite set of points $\omega \subset \mathbb{R}^N$, $N \in \mathbb{N}$ and number $k \in \mathbb{N}$, original k-means method [4] iteratively tries to approximate solution to k-partition problem. That is to partition set ω into k classes $\omega_1, \ldots \omega_k$ each corresponding with point $c_i \in \mathbb{R}^N$, $i = 1 \ldots k$ called centroid, in such way that

$$\sum_{i=0}^{k} \sum_{x \in \omega_i} \|c_i - x\|^2$$

is minimal. In our setting we used set of centers of gravity of the triangles in the mesh as a set ω. We modified the basic k-means method in two ways. First we ensure that each centroid is always a point from ω by placing it in the closest point in ω after each iteration. Second we assigned each point $x \in \omega$ a weight $w(x)$ equal to the surface volume of the corresponding triangle. The generalized algorithm iteratively minimizes expression [1]

$$\sum_{i=0}^{k} \sum_{x \in \omega_i} w(x) \|c_i - x\|^2.$$

This ensures that the partition does not depend on density of points of the mesh and surface of the muscle attachment is divided between muscle elements so that the variation of surface volumes assigned to elements is minimal, see Fig. 1.

Muscle elements' endpoints are calculated separately for origin and insertion. In order to place the muscle elements we need to connect corresponding endpoints so that lines of action not only do not intersect but also are not entangled. Our approach is based on Euclidean matching problem in two dimensions. It can be proven that the minimality of total pairing distance ensures that no two line segments connecting paired points intersect. This result transfers to three dimensions, however it is too weak. It does not guarantee that action lines do not run

across each other. Fortunately minimal matching still provides good results in which virtual muscle elements are not tangled with each other.

The minimal pairing is obtained by Hungarian algorithm [3] which finds minimal matching in weighted bipartite graph. In our case we are concerned with complete bipartite graph on two sets of centroids on origin and insertion surfaces. Euclidean distances are taken as weights of the edges. This graph is complete, hence it contains perfect matching and minimal matching always exists [3]. The resulting minimal matching with pairs connected by lines can be seen in Fig. 2. We used implementation found in [2].

Our study provides novel approach to acquiring data used in biomechanical models along with dataset of hand muscle data. It also provides a tool for generating these data, relieving researchers of some tedious labor and possibly allowing for greater reproducibility of research.
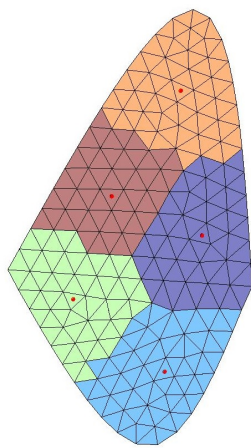

Fig. 1. Opponens pollicis insertion with five muscle elements endpoints and surfaces assigned to them colored
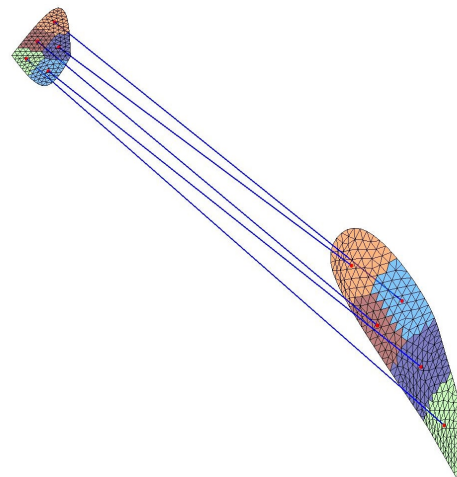
Fig. 2. Opponens pollicis connectivity with five muscle elements

References

[1] Bock, H.-H., Origins and extensions of the k-means algorithm in cluster analysis, Electronic Journal for History of Probability and Statistics 4 (2) (2008) 1-18.

[2] Cao, Y., Hungarian algorithm for linear assignment problems (V2.3). [online] https://www.mathworks.com/matlabcentral/fileexchange/20652-hungarian-algorithm-for-linear-assignment-problems-v2-3, 2011.

[3] Frank, A., On Kuhn's Hungarian method – A tribute from Hungary, Egervary Research Group, Pazmany P. setany 1/C, H1117, Budapest, 2004.

[4] MacQueen, J., Some methods for classification and analysis of multivariate observations, Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability (1967) 281-297.