34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

A Novel Spatiotemporal Muscle Activity Imaging Approach based on the Extended Kalman Filter*

Jing Wang, Yingchun Zhang**, Xiangjun Zhu, Ping Zhou, Chenguang Liu and William Z. Rymer

***Abstract*— A novel spatiotemporal muscle activity imaging (sMAI) approach has been developed using the Extended Kalman Filter (EKF) to reconstruct internal muscle activities from non-invasive multi-channel surface electromyogram (sEMG) recordings. A distributed bioelectric dipole source model is employed to describe the internal muscle activity space, and a linear relationship between the muscle activity space and the sEMG measurement space is then established. The EKF is employed to recursively solve the ill-posed inverse problem in the sMAI approach, in which the weighted minimum norm (WMN) method is utilized to calculate the initial state and a new nonlinear method is developed based on the propagating features of muscle activities to predict the recursive state. A series of computer simulations was conducted to test the performance of the proposed sMAI approach. Results show that the localization error rapidly decreases over 35% and the overlap ratio rapidly increases over 45% compared to the results achieved using the WMN method only. The present promising results demonstrate the feasibility of utilizing the proposed EKF-based sMAI approach to accurately reconstruct internal muscle activities from non-invasive sEMG recordings.**

I. Introduction

Surface Electromyogram (EMG) technology provides a non-invasive way for rapid monitoring muscle activities that aids in the diagnosis of neuromuscular disease. However surface EMG signal is composed of the superimposed action potentials of many muscle fibers and is the general picture of muscle activation as opposed to the activity of only a few fibers as observed using an inserted needle electrode in intramuscular EMG, which limits its application in clinic [1]. Muscle activity imaging (MAI) technology has been developed to characterize the specific muscle groups which are responsible for the discharged surface EMG recordings to overcome this limitation, and holds promise in advancing sEMG application in clinic. Most of traditional MAI technology is based on the spatial estimation approach [6, 7], and it suffers from limited imaging accuracy. A spatiotemporal muscle activity imaging (sMAI) approach is proposed in the present study using the Extended Kalman Filter (EKF) to accurately reconstruct internal muscle activities from non-invasive multi-channel sEMG recordings.

*Research supported in part by NIH K99DK082644 and NIH HD050821-08

Jing Wang is with the Department of Urology, University of Minnesota, Minneapolis, MN 55455 USA.

**Yingchun Zhang is with the Department of Urology, University of Minnesota, Minneapolis, MN 55455 USA. (phone: 612-625-7939; fax: 612-626-0428; e-mail: zhang320@ umn.edu).

Xiangjun Zhu is with the Department of Urology, University of Minnesota, Minneapolis, MN 55455 USA.

Ping Zhou is with the Sensory Motor Performance Program (SMPP), Rehabilitation Institute of Chicago (RIC), and the Department of Physical Medicine and Rehabilitation, Northwestern University, Chicago, IL 60611 USA.

Chenguang Liu is with the Division of Cardiology, School of Medicine, University of Alabama, Birmingham, AL 35294 USA.

William Z. Rymer is with the Rehabilitation Institute of Chicago (RIC), and the Departments of Physical Medicine and Rehabilitation, Physiology, and Biomedical Engineering, Northwestern University, Chicago, IL 60611 USA.

II. Methodology

In the forward solution, a distributed dipole source model is employed to model internal muscle activities [8], and a linear relationship between the source space and measurement space is established. In the inverse solution, an Extended Kalman Filter is employed to iteratively estimate the 3-dimensional (3D) distribution of internal muscle activities from the noninvasive sEMG measurements throughout a time period.

A. Distributed dipole source model

The 3D internal muscle activity space is described using a distributed dipole source space model, in which we assume that the current dipoles are evenly distributed over a fixed lattice covering the 3D muscle fibers, and the direction of dipole moment is fixed along the muscle fiber direction for each dipole. In the present study, a total number of 2048 ($16\times8\times16$) electric current dipoles is employed in the distributed dipole source space model. A total number of 225 (15×15) surface EMG electrodes is assumed over a planar skin surface which is 2 mm away from the muscle activity source space to record surface EMG signals (Fig. 1). The tissue between the muscle activity source space and the skin surface is assumed as a homogenous and anisotropic conducting volume limited by a plane (skin surface) of infinite extent [2]. The transverse and longitudinal conductivities of muscle are set as 0.063 and 0.378 s/m respectively and the conductivity of the skin and the tissue between skin and muscle is set as 0.063 s/m [3]. The relationship between the distributed dipole sources and the surface measurements can be described as

$$\Phi(t) = A*J(t) \tag{1}$$

where $\Phi(t)$ is a $M\times1$ vector containing the surface EMG measurements at time instant t, and M is the number of recording sites. $J(t)$ is a $N\times1$ vector containing dipole current densities at N grid points in the muscle activity source space at time instant t. A is a $M\times N$ transfer matrix relating the dipole current densities and the surface EMG signals.

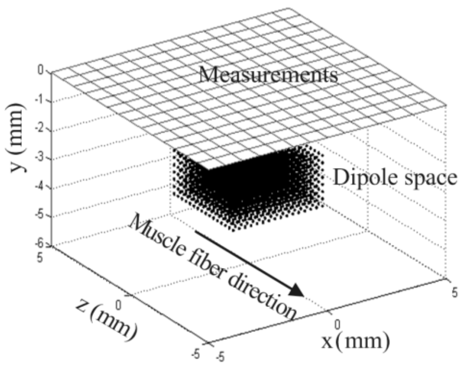

Figure 1. Dipole source space and measurements. The nodes on mesh represent recording sites and the dots represent dipoles in source space.

B. Extended Kalman Filter

The Kalman Filter is a set of mathematical equations that provides an efficient recursive method to estimate the state of a process by minimizing the error covariance [4]. The Extended Kalman Filter is designed for the situation when the relationship between source space and measurement space or the prediction of state is nonlinear [5].

A state-space model is developed in order to utilize the Kalman Filter to solve the ill-posed inverse problem in the proposed sMAI approach, and the state-space model is governed by the following equations

$$s_k = f(s_{k\text{-}1}) + u_{k\text{-}1} \quad (2)$$

$$\Phi_k = h(s_k) + v_{k\text{-}1} \quad (3)$$

where s_k is the state at M_t time instant ($N \times M_t$ matrix) at step k, and is the amplitudes of dipoles in this case. f is a processor which predicts states from previous states. Φ_k is the measurements at M_t time instant ($M \times M_t$ matrix) according to the state at step k. h is the linear operator defined in (1). $u_{k\text{-}1}$ and $v_{k\text{-}1}$ are process noise and measurement noise respectively at step k-1, which are assumed as independent Gaussian white noise normally distributed with zero mean and variances as Q and R.

$$P(u) \sim N(0, Q)\ ;\ P(v) \sim N(0, R). \quad (4)$$

In the proposed sMAI approach, f is a nonlinear processor developed based on exponential smoother defined as

$$s_{z,k} = \begin{cases} s_{zs}, & \text{when } |s_{z,k-1} - s_{zs}| > 0.1 \times s_{z,k-1} \\ s_{z,k-1}, & \text{when } |s_{z,k-1} - s_{zs}| \le 0.1 \times s_{z,k-1} \end{cases}. \quad (5)$$

$$s_{zs} = 0.05 \times s_{z-2,k-1} + 0.2 \times s_{z-1,k-1} + 0.5 \times s_{z,k-1} + 0.2 \times s_{z+1,k-1} + 0.05 \times s_{z+2,k-1}. \quad (6)$$

where z is the dipole index on muscle fiber direction, $s_{z,k}$ is the updated state at step k on position z, and $s_{z,k\text{-}1}$ is the state at step k-1 on position z. (6) is a smoother only works on muscle fiber direction.

$$s_{t,k} = \begin{cases} s_{ts}, & \text{when } |s_{t,k-1} - s_{ts}| > 0.1 \times s_{t,k-1} \\ s_{t,k-1}, & \text{when } |s_{t,k-1} - s_{ts}| \le 0.1 \times s_{t,k-1} \end{cases}. \quad (7)$$

$$s_{ts} = 0.05 \times s_{t-2,k-1} + 0.15 \times s_{t-1,k-1} + 0.6 \times s_{t,k-1} + 0.15 \times s_{t+1,k-1} + 0.05 \times s_{t+2,k-1}. \quad (8)$$

where $s_{t,k}$ is the updated state at step k at time instant t, and $s_{t,k\text{-}1}$ is the state at step k-1 at time instant t. (8) is a smoother in temporal space.

The initial state is characterized using the weighted minimum norm (WMN) regulation method for sEMG measurements at each time instant [9]. The iteration in EKF process stops when the change of state began to increase. The change of state (CS) was defined as

$$\mathrm{CS} = \left|\sum s_k - \sum s_{k-1}\right| / \left|\sum s_{k-1}\right|. \quad (9)$$

The final state is then utilized to reconstruct the internal muscle activities during the entire recording period which is tackled with the EKF.

C. Computer Simulation

Two active muscle fibers were assumed in the muscle activity source space with random position and length. One activity zone was assumed on each muscle fiber with random initial position, and muscle activities in the activity zone were simulated by 5 continuous current dipoles. The simulated muscle activity zones propagated along muscle fiber direction with a conduction velocity of 4 mm/ms [2] until they reached the edge of the assumed muscle activity space. Surface EMG measurements were simulated by calculating the potentials at each recording site generated by the assumed internal activating dipoles through the tissue space at each time instant [2]. sEMG measurements for 5 sampling time points were employed in the present computer simulation study to reconstruct internal muscle activities.

Both the localization error and overlap ratio are calculated to evaluate the performance of the proposed sMAI approach. The localization error is defined as the Euclidean distance between the geometric centers of simulated sources and reconstructed sources. In order to calculate the overlap ration, a 3×3×3 cubic is assumed for each simulated source dipole with the source dipole located at the center. The cubes of all the dipoles in the simulated muscle activity zone form a simulated muscle activity volume. The overlap ratio is calculated as the number of reconstructed dipoles which fall into the simulated muscle activity volume divided by the number of reconstructed dipoles.

III. Results

A series of computer simulations was conducted to test the performance of the proposed EKF-based sMAI approach. The results achieved with the proposed EKF-based sMAI approach were also compared with the results achieved with the WMN method.

Simulation results at a time instant are showed in Fig. 2a as a typical example. Results show that the localization error of the reconstructed sources during the iterations of EKF-based sMAI approach decrease by around 70% after the first iteration, while the overlap ratio of simulated sources and reconstructed sources increased to almost 3 times of the initial value. Then the localization error keeps decreasing until the 4th iteration and increases slightly after the 5th iteration. The overlap ratio keeps increasing until the 2nd iteration and starts to decrease slightly at every iteration after that. In this case, the iteration process should stop at the 4th iteration according to CS described in (9), and the results after the 4th iteration are used for comparison. Note that the localization error and overlap ratio at the initial state in Fig. 2a are actually for the reconstructed results achieved by the WMN method. We can see the EKF-based approach significantly improve the reconstruction accuracy compared to the WMN method.

The average value of normalized localization errors and the overlap ratios at 30 time instants in all the 6 trails are compared for the WMN and EKF-based approaches and are summarized in Fig. 2b. Results show that the average localization error decreases significantly from 1.37±0.34 mm to 0.89±0.23 mm (T-test, $P<0.005$, n=30), which is decreased by over 35% of the value in initialization. On the other side, the average overlap ratio increases significantly from 0.6±0.38 to 0.88±0.15 (T-test, $P<0.001$, n=30), which is increased by more than 45% of the value in initialization.

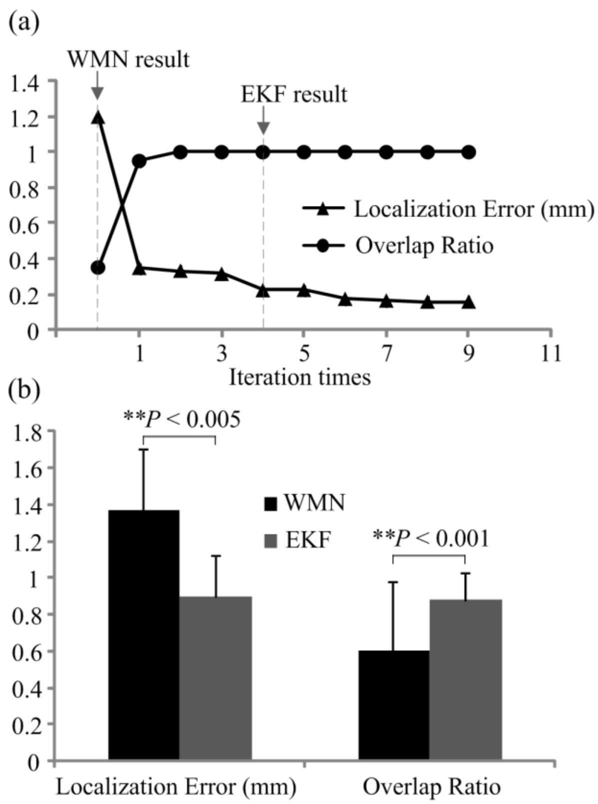

Figure 2. The variation of localization error and overlap ratio in EKF from results at one time instant (a) and the comparison of average localization error and average overlap ratio between the results of WMN and the results of EKF (b).

IV. DISCUSSION

Preliminary results demonstrate the feasibility of utilizing the proposed spatiotemporal imaging approach to accurately reconstruct internal muscle activities from noninvasive surface EMG recordings.

In proposed imaging approach, a new nonlinear state predictor, which is the most important step in the EKF, is designed specifically for muscle activity imaging approach. According to the propagating feature of muscle activities, potential continuity holds in both temporal space and spatial space along the direction of muscle fiber. Based on these electrophysiological features, the new state predictor is established by smoothing the state in temporal space as well as along muscle fiber direction. The smoothing coefficients are calculated based on exponential smoother to make mild changes in state, as described in (6) and (8). Although the prediction of state is mild, the results converged rapidly during iterations (Fig. 2a). The significant reduce of localization error and increase of overlap ratio (Fig. 2b) demonstrated in the simulation results indicate significant improvement on imaging accuracy achieved by using the new approach.

ACKNOWLEDGMENT

This work was supported in part by NIH K99DK082644 and NIH HD050821-08. The authors would also like to thank Dr. Gerald Timm in the Department of Urology at the University of Minnesota Medical School for useful discussion.

REFERENCES

[1] G. Drost, D. F. Stegeman, B. G. van Engelen, and M. J. Zwarts, “Clinical applications of high-density surface EMG: A systematic review,” *J. Electromyogr. Kinesiol.*, vol.16, pp. 586-602, Dec. 2006.

[2] R. Merletti, L. Lo Conte, E. Avignone, and P. Guglielminotti, “Modeling of Surface Myoelectric Signals-Part I: Model Implementation,” *IEEE Trans. Biomed. Eng.*, vol. 46, pp. 810-820, Jul. 1999.

[3] J. Duchene and J. Y. Hogrel, “A model of EMG generation,” *IEEE Trans. Biomed. Eng.*, vol.47, no.2, pp.192-201, 2000.

[4] G. Welch and G. Bishop, “An Introduction to the Kalman Filter,” *Citeseer*, vol. 7, pp. 1-16, Jul. 2006.

[5] C. Liu and B. He, “Non-invasive Estimation of Global Activation Sequence using Extended Kalman Filter,” *IEEE Trans. Biomed. Eng.*, vol. 58, pp. 541-549, Mar. 2011.

[6] Y. Zhang, D. Wang and G. W. Timm, “A three-dimensional muscle activity imaging technique for assessing pelvic muscle function,” *Inverse Problems*, vol. 26, no. 11, Oct. 2010.

[7] K. van den Doel, U. M. Ascher and D. K. Pai, “Computed myography: three-dimensional reconstruction of motor functions from surface EMG data,” *Inverse Problems*, vol. 24, no. 6, Nov. 2008.

[8] Y. Zhang, W. van Drongelen, M. Kohrman, and B. He, “Three-dimensional brain current source reconstruction from intra-cranial ECoG recordings,” *Neuroimage*, vol. 42, pp. 683-695, Aug. 2008.

[9] Y. Zhang, L. Ding, W. van Drongelen, K. Hecox, D. Frim, and B. He, “A Cortical Potential Imaging Study from Simultaneous Extra- and Intra-cranial Electrical Recordings by Means of the Finite Element Method,” *Neuroimage*, vol. 31, pp. 1513-1524, Jul. 2006.