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Effect of shoulder angle variation on sEMG-based elbow joint angle estimation

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ABSTRACT

For the decade now, surface electromyogram (sEMG) signal has been extensively applied in joint angle estimation to control the prostheses and exoskeleton systems. However, the sEMG signal patterns can be severely affected by shoulder angle variations, which restricts its applications to a practical use. In our study, we evaluate the effect of shoulder angle variations on elbow angle estimation performance. This adverse effect increases mean root mean square (RMS) error by 14.85° in our experiment. Then, four estimation methods are proposed to solve this problem: (1) using a training set including all shoulder angles' training data to train model; (2) adding two shoulder muscles' sEMG as additional inputs; (3) a two-step method using arm muscles' sEMG and two shoulder muscles' sEMG; and (4) a two-step method using arm muscles' sEMG and measured shoulder angle value by a motion sensor. 13 subjects are employed in this study. The experimental results demonstrate that the mean RMS error is reduced from 21.36° to 12.85° in method one, 9.84° in method two, 7.67° in method three, and 6.93° in method four, respectively. These results show that our methods are effective to eliminate the adverse effect of shoulder angle variations and achieve a better elbow angle estimation performance. Furthermore, this study is helpful to develop a natural and stable control system for prostheses and exoskeleton systems.

1. Introduction

As a non-invasive technology, surface electromyogram (sEMG) signal can be used for an interaction way between people and environment efficiently and friendly in daily life (Lorrain et al., 2011). Since sEMG directly shows the real-time activity level of muscles (Su et al., 2013; Tang et al., 2014a), many previous studies applied sEMG in joint angle estimation to control the prostheses and exoskeleton systems (Sylos-Labini et al., 2014; Kiguchi and Hayashi, 2012; White et al., 2017; Brunelli et al., 2015; Tang et al., 2014b; Farina et al., 2014; Fougner et al., 2012; Theurel et al., 2018). The overall control architecture of these applications can be generalized as: (1) preprocessing the sEMG signals to remove the noise or artifacts, (2) extracting various types of features, (3) feeding these features into a trained estimation model to identify an angle, and (4) conveying a control signal transformed from the output of the model to the device.

Most studies on sEMG-based joint angle estimation to control the prostheses and exoskeleton systems mainly aim to obtain a better off-line estimation performance according to algorithm improvement in feature extraction and estimation process (Ngeo et al., 2013; Valentini et al., 2015; Araki et al., 2013; Yang et al., 2017). Some methods can achieve a extremely good estimation performance (higher than 95% accuracy) (Erik Scheme and Kevin Englehart, 2011). However, previous efforts towards sEMG-based joint angle estimation were under predefined experimental setting (Farooq and Khan, 2014). Some external factors, like limb position variations (Scheme et al., 2010), force variations (Al-Timemy et al., 2016; Tang et al., 2016), electrode displacements (Cipriani et al., 2012) and electrode locations (Hwang et al., 2014), can affect the sEMG signals collection and make a worse estimation performance in practical use. Besides, the elbow angle estimation performance may be affected by the shoulder angle variations significantly. For example, in the experimental state, the arm sEMG signals are always collected at a predefined shoulder angle for each subject, which is easy to perform repeatable contractions and acquire stable training data (Fougner et al., 2011); in practical use, more unpredictable shoulder angles may happen due to the various upper-limb movements in daily life, which degrades the estimation performance deriving by physiological variations of muscles. Some researchers have turned their attention to investigate the impact of upper-limb position on performance of sEMG-based pattern recognition systems. Scheme

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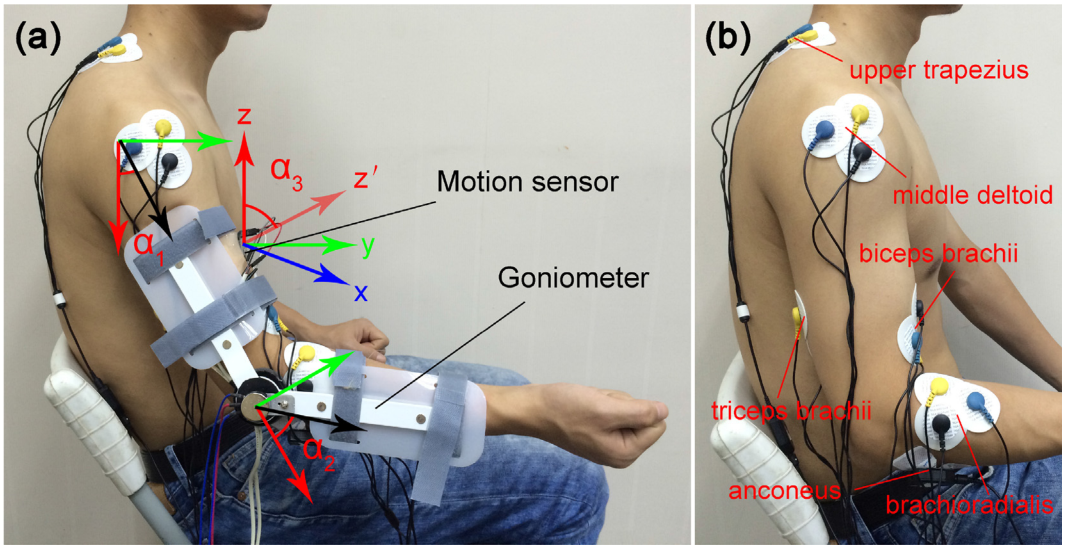

Fig. 1. Experimental setup (a) and electrode position (b). Shoulder angle is represented by α_1. Elbow angle is represented by α_2. The angle between motion sensor's z-axis and natural coordinates' z-axis is represented by α_3. The motion sensor was used to measure the shoulder angle in Method four, which was placed about 10 cm from the elbow joint on the midline of the upper arm. The goniometer was made by ourselves to acquire the actual elbow angle. It consists of a potentiometer, two metal bars, a rotation axis and four belts.

et al. (2010) used the training data and testing data from the same or different limb positions to train sEMG-based classification models, and found that limb position variations led to a significant increase of sEMG classification error from 6.9% to 35.0%. Jiang et al. (2013) demonstrated that changing arm position adversely influences the prediction performance of kinematics from sEMG, and the experimental results showed the intra-position R^2 values were significantly higher than the corresponding inter-position values ($p < 0.001$). However, few studies have investigated the performance of elbow angle estimation if the shoulder angle changes.

In a traditional way, elbow angle can be estimated using sEMG signals from several arm muscles (Luh et al., 1999; Tang et al., 2014b; Raj and Sivanandan, 2015). But since shoulder angle information cannot be acquired from sEMG of these arm muscles directly, it is difficult to deal with the adverse effect of shoulder angle using a traditional sEMG-based estimation method. The similar limitation also happens in the effect of arm position on sEMG-based gesture recognition. Several studies have focused on the additional inputs and novel estimation scheme. Geng et al. (2012) used sEMG sensors and a mechanomyogram (MMG) sensor to solve the effect of limb position on motion classification for real-time prostheses control, and achieved a maximum increase of completion rate from 81.4% to 94.3%. Park et al. (2016) applied the ensemble-learning method to propose a position-independent decoding model to estimate the likelihood of different arm positions, which could successfully decode four wrist movements in different arm positions. In addition, not many efforts aimed to solve the effect of shoulder angle on elbow angle estimation. Fougner et al. (2011) used sEMG sensors and two accelerometers to eliminate the effect of arm position and shoulder angle on sEMG pattern recognition, but like most previous studies, this study mainly focused on different arm positions (only three different shoulder angle were considered). Boschmann et al. (Boschmann and Platzner, 2013) applied a high density electrode array to reduce the shoulder angle effect in distinguishing different hand and wrist movements, but this method using an electrode array (including 96 sEMG sensors) cost too much.

In this paper, we firstly evaluate the adverse effect of shoulder angle variations on elbow angle estimation. For solving this problem, we propose four methods:

1) Method one: using a training set including all shoulder angles' training data to train model.
2) Method two: adding two shoulder muscles's sEMG as additional inputs. Shoulder angle value can be estimated by shoulder muscles's sEMG. This lets the estimation model include more kinds of training data, and increases the input vectors' space dimensionality.
3) Method three: a two-step method using arm muscles' sEMG and two shoulder muscles' sEMG. There are two steps in this method: in step 1, the shoulder muscles' sEMG data are classified to get a specific shoulder angle; in step 2, the corresponding pre-trained model in the evaluation stage using the same shoulder angle's training data is used for elbow angle estimation.
4) Method four: a two-step method using arm muscles' sEMG and measured shoulder angle value by a motion sensor. There are two steps in this method: in step 1, the motion sensor data are classified to get a specific shoulder angle; in step 2, the corresponding pre-trained model in the evaluation stage using the same shoulder angle's training data is used for elbow angle estimation.

2. Methods

2.1. Subjects

13 male able-bodied subjects (age range: 26 ± 3 years, height range: 172 ± 6 cm, weight range: 65 ± 5 kg) were volunteered to participate in our experiment. The ethical committee of Zhejiang University reviewed our experimental protocol and approved it. All subjects were informed not to perform any intense movements to avoid fatigue on the day of experiment, and they all signed the informed consents prior to the experiment.

2.2. Experimental procedure

When subjects arrived, one experimenter helped them attach the sensors (sEMG sensors, motion sensor and goniometer) on the right arm and ensured that the signals were normal according to the signal check procedures from Konrad (2005). The signal check procedures included the skin impedance test (impedance range keeps in 1-5Kohm) and the visual inspection of the raw EMG baseline (the average noise level should be located at 1–3.5 μV, and the baseline should remain at the zero line). Then, subjects sit on a chair to perform flexion-extension movements of elbow in the sagittal plane (Fig. 1(a)). The elbow angle range (α_2) was from 0° to 90°. 0° represented full extension, and 90°