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Surface EMG-based Surgical Instrument Classification for Dynamic Activity Recognition in Surgical Workflows

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Abstract: We introduce a wearable-based recognition system for the classification of natural hand gestures during dynamic activities with surgical instruments. An armband-based circular setup of eight EMG-sensors was used to superficially measure the muscle activation signals over the broadest cross-section of the lower arm. Instrument-specific surface EMG (sEMG) data acquisition was performed for 5 distinct instruments. In a first proof-of-concept study, EMG data were analyzed for unique signal courses and features, and in a subsequent classification, both decision tree (DTR) and shallow artificial neural network (ANN) classifiers were trained. For DTR, an ensemble bagging approach reached precision and recall rates of 0.847 and 0.854, respectively. The ANN network architecture was configured to mimic the ensemble-like structure of the DTR and achieved 0.952 and 0.953 precision and recall rates, respectively. In a subsequent multi-user study, classification achieved 70 % precision. Main errors potentially arise for instruments with similar gripping style and performed actions, interindividual variations in the acquisition procedure as well as muscle tone and activation magnitude. Compared to hand-mounted sensor systems, the lower arm setup does not alter the haptic experience or the instrument gripping, which is critical, especially in an intraoperative environment. Currently, drawbacks of the fixed consumer product setup are the limited data sampling rate and the denial of frequency features into the processing pipeline.

Keywords: Natural User Interface, Gesture Recognition, Workflow Recognition, EMG Processing, Machine Learning

1 Introduction

The digital operating room (OR) is a highly outcome- and cost-driven environment and personnel, and hospital providers are continuously challenged to improve operation quality and efficiency. In response, one aspect of optimization is to recognize the intraoperative workflow based on the surgical work steps or used resources, like surgical instruments. There exists a wide range of employed technologies, e.g. cameras, scales as well as force, RFID and acceleration sensor, that involve some form of mounting or fixation to the OR instrumentation [1,2]. The main drawbacks are the limited line of sight into the work area, sensor contamination, as well as limited stationary acquisition capabilities and handling overhead for medical personnel. With already limited space and time resources in the OR, touchless applications were introduced for the various tasks in the medical domain [3]. Yet in the operating room, the functionalization of wearables for the identification of surgical tasks, e.g. using the recognition of natural user gestures, is still unexploited. We, therefore, present an approach for a wearable-based recognition system using multi-EMG data of the surgeon's lower arm movement. The system uses a circular sensor setup to acquire activity data of the surgeon through grasping information of the lower arm during usage of surgical instruments. We assume that the usage of a specific surgical instrument induces distinguishable recruitment of muscle groups, that is superficially measurable. We provide a proof-of-concept study and first multi-user classification, outlining the potential of the classification approach.

2 Methods & Material

2.1 Instrument Selection

Since the number of surgical instruments to cover is far too large and would exceed and diminish the explorational character of the work, we limited the selection to instruments

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with distinct types of usage (Tab.1). Following the taxonomy from [4], we selected instruments from general surgery groups for (I) cutting and dissecting, (II) clamping and occluding and (III) grasping and holding. Additionally, we differentiated between a passive and active mode of instrument usage. The passive mode is defined by the characteristic holding gesture performed with the hand after picking up the instrument without additional actions to exclude hand movement usually covered by interacting with the scrub nurse. The active mode is defined by the characteristic hand gestures performed to apply the instrument functionality to the situs. All selected instruments can be distinguished in terms of occupied hand parts as well as the duration of active usage.

Table 1: Overview of used surgical instruments and their corresponding type and movement characteristics

Instrument	Instrument Type [4]	Hand Movement Characteristic (Gripping Force Duration)
Straight Clamp	Clamping & Occluding, Grasping & Holding / Hook	Ring finger against thumb (spontaneous)
Forceps	Grasping & Holding / Hold	Index and middle finger against the thumb (continuous)
Perforator	Cutting & Dissecting / Pinch	Index finger against thumb (continuous)
Bone Punch	Cutting & Dissecting / Punch	All fingers against thumb (spontaneous)
Sharp Spoon	Cutting & Dissecting / Carve	Index finger against the thumb, extensive wrist movement (continuous)

2.2 Signal Acquisition

For the signal acquisition, we used a commercially available Myo Gesture Control Armband (Thalmic Labs, USA), a wireless multi-sensor armband with an 8-channel circular EMG sensor setup. Each sensor uses three dry electrodes of medical grade stainless steel for reference mass-based surface measurement with a fixed sample rate of 200 sps. Concerning sEMG measurement standards, the armband is placed on the prominent bulge of the lower arm where the main muscle mass is formed [6]. With an expandable band diameter between 19 and 34 cm and less than 100g weight, the armband is highly flexible and unobtrusive for the user. The Myo supports raw EMG sensor data acquisition based on a

Figure 1: The signal processing pipeline with the main work steps: (a) Instrument selection, (b) lower arm signal acquisition, (c) EMG channel correspondence, (d) signal processing and feature extraction and (e) classification.

Bluetooth master client connection. Using the circular EMG setup of the Myo, we were able to measure the superficial lower arm muscle activity of interest occupied during hand, and finger and wrist movements. The use of a specific surgical instrument and the corresponding generation of sEMG-signals will subsequently be called as instrument activity.

Surgical instrument activities were measured for one user in a proof-of-concept study followed by six users in a follow-up study. For each user, the acquisition was performed in one session and with minimal pauses to compensate for sEMG variability and sensibility as well as intrinsic acquisition errors [7]. Each instrument activity was performed within a timespan of four seconds, followed by a rest phase of four seconds to improve signal separation leading to 15 unique datasets per instrument and usage mode, respectively. We used the quadrated, absolute raw channel data and smoothed with a moving average-filter ($W=50$). All signal processing actions were performed using MATLAB 2016b.

2.3 Feature Selection & Classification

Based on the understanding of muscle physiology, we expected a causal relationship between different instrument activities and generated lower arm muscle potentials. Initially, we investigated the occurrence of unique sEMG signal curves with minimal cross-correlation of EMG channels with a standard algorithm for discrete cross-

correlation. Subsequently, feature definition and analysis steps were performed on these unique channels based on established feature sets for gesture-based sEMG-signal classification [8]. We tested ten different features in the time domain to characterize statistical as well as shape-related signal properties. Power spectra and density functions were investigated, however, since spectral components of muscle sEMG-signals range between 0 to 500 Hz [9] a significant part of higher frequency information could not be acquired due to the limited sampling rate of the EMG sensors. Emphasis was thus put on the time series analysis of the instrument activities. For the identification of key features for instrument classification, dependent two-sided t-tests and one-way variance (ANOVA) testing over all calculated feature sets for all instrument activities were performed. For the signal classification, observation sets were generated using the identified unique features (7 features x 5 channels). Each classifier was then trained and validated based on a 5-fold cross-validation method. We initially chose a Bagging-Ensemble decision tree approach with a forest set of $C = 30$ trees (Fig.2) due to the algorithms' robustness and low computational cost.

Figure 2: Overview of the employed artificial neural network architecture. A hidden layer α_i is locally connected to a following hidden layer, forming a smaller subnetwork of 2 layers inside the ANN superstructure.

Additionally, we investigated a way to introduce DTR-Ensemble-like training behaviour into a multi-layer ANN. Similarly, to CNN architectures, we used local connectivity of consecutively connecting hidden layers forming parallel subnetworks of layers that feed into a final output layer (Fig. 3). ANN training was performed with a tanh-transfer function for neurons and Bayesian Regularization (BR) as the objective function. Input vectors consisted of the feature subsets, and feature values were normalised to a range of $[-1, +1]$ to support transfer function properties and to avoid value training errors. We hypothesised a similar training

behaviour to Bootstrapping-Ensemble-Approaches for DTR learning.

3 Results

The investigation of channel-related signals during instrument usage showed the most prominent activations for channels 3, 4 and 5 for all instruments. Channels 6, 7 and 8 showed increased activation mainly for the forceps, straight clamp and bone punch. Channel 2 was most sensitive for perforator and sharp spoon activities. Channel 1 noticeably had no traceable signal activation over all recorded activities. The cross-correlation of channel data showed that channels 4-7 had the lowest similarity values across all instrument activities. The mean and variance analysis for signal features identified the mean waveform length (mWL) as the most expressive property for all instruments, followed by a log detector (LOG) and signal variance (VAR). Overall, seven features were then used to form the feature vector for the subsequent classification studies.

Table 2: Results for the signal analysis of unique EMG channels and most expressive signal features. (mWL – mean waveform length, LOG – log detector, SSC – sign slope change, VAR – variance)

Instrument	Active EMG Channels	Unique Channels	Unique Features
Straight Clamp	2-6	6	mWL, LOG, SSC
Forceps	2-5, 7	7	mWL, VAR
Perforator	2-6	5	mWL, LOG
Bone Punch	2-6	4	mWL, LOG
Sharp Spoon	2-5	5	mWL, LOG

For the classification approaches, precision and recall rates were calculated from the 5-fold cross-validation for both the proof-of-concept and the follow-up group. In both studies, the ANN performed better than the DTR across all instruments. For both studies, the highest precision and recall rates were achieved for active modes of the bone punch followed by the forceps. Lowest classification rates were reached for the perforator and the sharp spoon. Overall, the classifiers showed considerable precision and recall loss in the classification of passive bone punch and active, sharp spoon activity.

Table 3: Results for the signal classification for the proof-of-concept and follow-up studies. Precision and recall rates are averaged over both activity modes.

Study	Classifier	Precision	Recall
Proof-of-Concept (n=1)	DTR	0.847	0.854
	ANN	0.952	0.953
Follow-Up (n=6)	DTR	0.622	0.640
	ANN	0.701	0.712

4 Discussion

Compared to exclusively hand-mounted sensor systems, the armband setup does not alter the haptic experience or the instrument gripping, which is critical, especially in an intraoperative environment [3]. The number of employed sensors is comparable to other setups for sEMG-based muscle activity classification [8]. Preparation of skin should be considered for future studies but is ultimately a drawback for ease-of-use in the preparation phase for surgery. Raw signal data was not normalised due to the constraints of intraindividual measurement in a single recording session. However, noise generation due to lower arm movement, accumulating muscle fatigue during the recording session as well as untreated skin preparation could potentially affect signal acquisition quality. The predetermined sample rate denies the acquisition of muscle activity signals [8]. Thus, a considerable part of the expected signal frequency spectrum could not be included for signal analysis. The classification results of the proof-of-concept study reveal that the apparent physiological difference for using surgical instruments can be identified using an EMG sensor setup. However, the follow-up study revealed that likely due to strong interindividual differences, the current DTR and ANN classifiers are not adequately tailored towards a multi-user recognition application. Consequently, alternate classifier approaches, e.g. for time series prediction, should be employed to exploit sequential information and connectedness of signal features during surgical instrument usage.

5 Conclusion

We successfully implemented a signal analysis and classification pipeline that enables the recognition of specific used surgical instruments using a commercially available

multi-EMG-sensor armband. To our knowledge, no recognition system currently employs EMG sensors for the classification of surgical activity. The disadvantages of the armband system as a consumer product lie in the limited biosignal acquisition capabilities and need to be compensated using more sophisticated classification approaches. Future work will address classification improvements for larger study groups.

Author Statement

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