Transfer Learning Framework for Early Detection of Fatigue Using Noninvasive Surface Electromyogram Signals (SEMG)

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Abstract

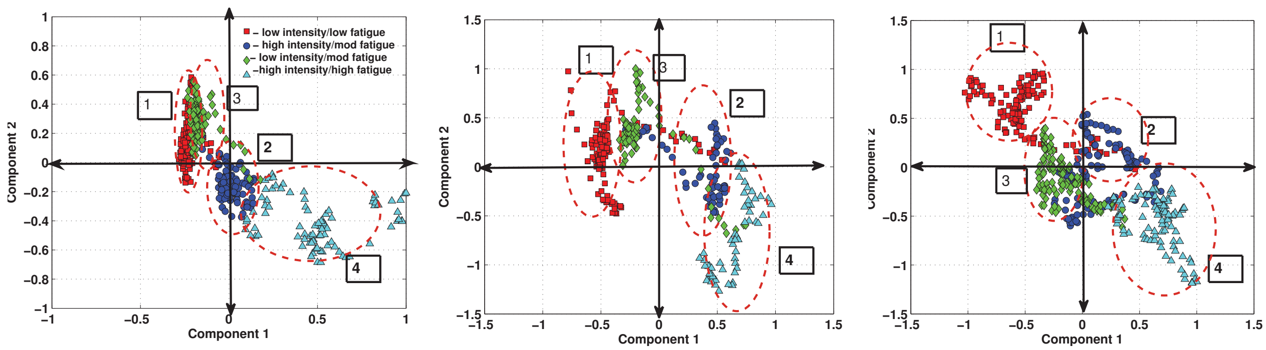
A multi source domain adaptation based learning for addressing subject based variability in myoelectric signals (SEMG), enabling generalized framework for detecting stages of fatigue.

Extended Abstract

Surface Electromyogram (SEMG) signals are physiological signals processed to assess the intensity of activity and the fatigue state of the muscles, non-invasively (Kumar, Pah, and Bradley 2003; Georgakis, Stergioulas, and Giakas 2003; Koumantakis et al. 2001; Gerdle, Larsson, and Karlsson 2000). However researches observed significant difference between the data collected from different subjects though they performed the same activity under similar experimental conditions (Contessa, Adam, and Luca 2009; Gerdle, Larsson, and Karlsson 2000). Because of their highly subject specific nature the SEMG based fatigue assessment requires subject specific calibration and are hence confined to clinical environments related to training and rehabilitation. A generalized framework for detecting different stages of fatigue would enable a wider deployment of SEMG in broader applications including muscle health monitoring in every day movement, industrial work, geriatric care etc. Such a system would also be able to detect fatigue at an early stage, thus preventing many of the accidents caused due to fatigue and the consequential medical cost and loss of life. The greatest challenge in developing generalized framework for physiological signals is subject based variability, which causes differences in data distribution across subjects. Consecutively, most of the classification frameworks, dealing with physiological signals have moderate to poor generalization across subjects (Leon et al. 2007),(Kim and Andre 2008). In the quest to address this challenge and develop a generalized framework for early detection of fatigue from SEMG signals, we propose a new multi source domain adaptation method, based on 'Transfer Learning' methodologies, which addresses the distribution difference between the subject data and enables knowledge transfer across subjects leading to the design and development of a generalized framework for a highly subject specific physiological signal.

Traditional machine learning algorithms assume that Training data X represents the population of a domain exhaustively and test data is i.i.d. drawn from the population of the same domain. The learning task is then to determine a hypothesis h that best represents the concept over the entire population X. The fundamental assumption being, any hypothesis found to approximate well over a sufficiently large set of training examples will also approximate well over other unobserved examples (Mitchell 1997), belonging to the same distribution as the training data. But if this basic assumption is violated as in the case of SEMG data over multiple subjects, direct application of traditional data mining and machine learning methods would not work. Figure 1 shows a typical distribution of SEMG data for three different subjects, collected over a fatiguing exercise at varying speed representing the four physiological phases corresponding to four classes (l) *low intensity of activity and low fatigue*, (2) *high intensity of activity and moderate fatigue*, (3) *low intensity of activity and moderate fatigue* and (4) *high intensity of activity and high fatigue*. The data distribution shown in Figure 1 is of factor scores obtained as a result of factor analysis done on the twelve dimensional feature vectors derived from raw SEMG signals. The details of the feature vectors, and the factor analysis results can be found in our earlier papers at (Chattopadhyay, Panchanathan, and Pradhan 2010; Pradhan, Chattopadhyay, and Panchanathan 2010; Chattopadhyay, Pradhan, and Panchanathan 2009). We observed that data distribution during each stage or class varies from subject to subject. This variation leads to predominantly conditional probability differences across subjects .

There has been several domain adaptation methodologies suggested so far in literature to address the differences in distribution so as to be able apply the traditional learning algorithms. But most of this work is primarily addressed towards reducing the gap in marginal probability differences. Shimodaira et al (Shimodaira 2000) biased the training samples by their test-to-training ratio to match the marginal distribution of the test data. Sugiyama et al (Sugiyama et al. 2008) tried to reduce the gap in marginal probabilities by minimizing the KL-divergence between test and weighted training data and Bickel et al (Bickel, Brückner, and Scheffer 2009) by discriminating training against test data with a proba-



(a) Subject 1 (b) Subject 2 (b) Subject 4

Figure 1: Three sample subjects (subjects 1, 2, 4) with four classes (four physiological stages) in our SEMG data set: Differences in marginal probabilities with conflicting conditional probabilities.

bilistic classifier. There are several other methods based on marginal probability differences only, Huang et al (Huang et al. 2007) re-weights the instances in source domain so as to *minimize* the marginal probability difference between the source and target domain, referred as *Kernel Mean Matching (KMM)*, using Maximum Mean Discrepancy (MMD) (Borgwardt et al. 2006) as the measure. Method suggested by Pan et al (Pan et al. 2009) is based on feature mapping so as to reduce the marginal probability differences between the source and target distribution based on minimizing MMD, referred as *Transfer Component Analysis (TCA)*. Domain adaptation machine suggested by Duan et al (Duan et al. 2009) is also based on marginal probability differences measured using MMD as the metric. There has been some work addressing conditional probability differences, but it is very limited. Gao et al (Gao et al. 2008) addresses conditional probability differences between the distributions, but this approach is restricted by the assumption that the test data follows a 'clustering' manifold. There is yet another approach suggested by Zhong et al (Zhong et al. 2009) which addresses both marginal and conditional probability differences between the distributions, referred as *KMapEnsemble (KE)*, based on domain mapping using Kernel Discriminant Analysis, followed by cluster based instance selection. This methodology assumes a clustering manifold in the mapped domain. Also, except the frameworks suggested by Gao et al (Locally Weighted Ensemble) and Duan et al (Domain Adaptation Machine) all other domain adaptation methodologies are single domain based.

In order to address the difference in distributions across subjects, we propose a multi source domain adaptation methodology based on predominantly conditional probability differences between the source and target distributions. The proposed target function is learned using a few labeled and unlabeled samples of the test subject data, labeled using an unsupervised conditional probability based weighing scheme. The proposed weighing scheme computes the similarities or weights between the target domain data and the different auxiliary sources (formed by different subject data) in a joint optimization framework, thus taking into account the interaction among the multiple auxiliary sources. This unique feature in our framework helps in addressing conflicting conditional probabilities between the sources leading to generating labels for the target domain data with higher accuracies compared to those obtained using methodologies based on weights computed independently for each source (Duan et al. 2009; Gao et al. 2008). Also since each class has different similarities and dissimilarities across the subjects as shown in Figure 1, hence different weights (with respect to target subject) are computed for each class for each subject data in the source domain.

We validated our framework on Surface Electromyogram signals collected from eight people during a repetitive gripping activity. We extracted 12 amplitude and frequency domain features from the SEMG signal. Comprehensive experiments on the SEMG data set demonstrate that the proposed method improves the subject independent classification accuracy by 32% to 37 % over the cases without any transfer learning. We implemented many of the existing popular domain adaptation methodologies on the SEMG data and proved the requirement of a multi source approach addressing conditional probability differences in addition to marginal probability differences. The proposed multi source transfer learning methodology outperforms the existing multi source as well as single source domain based methodologies.

We also suggested a new feature selection technique based on robustness to subject based variability. This technique provided a gain of 10% to 18% on the subject independent classification accuracies. The details of the feature vectors, the statistical tool used to measure subject based variability in features is presented in detail in our paper (Chattopadhyay, Pradhan, and Panchanathan).

Further, we have also deployed a fatigue grading framework for real time monitoring and grading the physiological state of the subject. The PC based system reads in the SEMG signals from the SEMG sensors placed on the subject muscle, over a USB port, processes it and displays the status of fatigue and intensity level on a scale of 0 to 1 on the monitor at real time. This work has been explained in detail in our earlier paper at (Chattopadhyay, Panchanathan, and Pradhan 2010).

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