An Overview of Electromyographic Signal Analysis

Alexandru STANCIU
National Institute for Research and Development in Informatics - ICI Bucharest
alexandru.stanciu@ici.ro

Abstract: This study presents an overview of electromyographic signal (EMG) based on a literature survey, describing the principal analysis methods and applications, such as motion prediction, monitoring eating behavior, and control of hand orthosis. A particular interest is dedicated to the emotion recognition use case and whether electromyography can be used to combat phishing attacks, as emotions influence human behavior, and human error, provoked or not, is the weakest link in cybersecurity.
Keywords: Electromyographic Signal, Signal Analysis, Phishing, Emotion Recognition, Pattern Recognition

INTRODUCTION

Biomedical signals such as electrocardiogram signal, electroencephalogram signal or electromyographic signal reflect the electrical activity of a specific part of the human body. As such, electrical activity provides information about a person's physiological condition. Traditionally, this information can be used by medical practitioners to make medical decisions. These decisions have important consequences for diagnosis, treatment monitoring, drug efficacy tests and quality of life.

From the perspective of an expert system, a doctor is an intelligent agent who makes optimal decisions, however, a certain degree of knowledge is needed to reach these decisions. This knowledge forms the process that generates actions depending on the current state and the information received from the environment (Faust et al., 2018).

This literature study presents an overview of the EMG signal analysis and some of its applications, such as motion prediction or control of prosthetic devices. Special consideration is dedicated to the emotion recognition use case and its implications for the cybersecurity domain, particularly regarding phishing attacks. The rest of the article is organized as follows. Section 2 describes the main techniques for EMG signal analysis. In Section 3, some applications of EMG analysis are presented, and a discussion related to emotional susceptibility from an emotional perspective is provided in Section 4. The conclusive remarks are expressed in Section 5.

ELECTROMYOGRAPHIC SIGNAL ANALYSIS

The electromyographic (EMG) or myoelectric signal is an electrophysiological signal generated by a muscle contraction that propagates spatially through the body. The origin of the myoelectric signal is the depolarization and repolarization of the cell membrane from muscle fibers during a contraction that causes the circulation of ionic currents, creating measurable action potentials in the body.

The signal represents thus the electrical impulse that produces the contraction of muscle fibers in the body - the skeletal muscles that control voluntary movements. The frequency of electromyographic signals can have a range between a few Hertz to about 300 Hz. The voltage can have a range between 10 microvolts and 1 millivolt.

In general, electromyographic signals are detected by using electrodes that are put on the skin or inserted directly into the muscles. Two electrodes are used to measure the voltage between them, and a third electrode is used to cancel the noise that may interfere with the signals of the other two electrodes (Raqeeb Technology Blog, n.d.).

The individual muscle fibers are innervated in groups by a single axon. This functional unit, consisting of the group of muscle fibers, axon and cell body of the nerve in the spinal cord, is called the motor unit (MU) and the action potentials of motor units (MUAP) are the result of innervation by the peripheral nerve and overlap to form a myoelectric signal that can be measured on the skin surface using surface electrodes or under the skin using invasive techniques (Hargrove et al., 2007).

Techniques for Electromyographic Signal Analysis

EMG signal analysis based on signal pattern recognition was initially investigated in the late 1960s and early 1970s. These early systems used characteristics amplified by signal amplitude and a statistical classifier to obtain a 75% classification accuracy for a problem with four classes.

Their main disadvantages were the large number of EMG channels, cumbersome equipment and long processing times. In the late 1970s and early 1980s, autoregressive coefficients were investigated as a set of signal characteristics and managed to achieve a classification accuracy of about 85% in a three-class problem, while reducing the number of EMG channels to two or four. However, computing technologies at that time failed to achieve this classification in real time (Hargrove et al., 2007).

In the early 1990s, Hudgins et al. (1993) showed that the surface EMG signal has a deterministic structure during the initial phase of muscle contraction. They proposed the use of time domain (TD) statistics elements as vector inputs for a two-layer neural network classifier (ANN). Using a single surface EMG data channel, this system was able to classify five states with an accuracy of approximately 92%.

Furthermore, a built-in controller has been constructed to implement this control scheme with an acceptable time delay of less than 300 ms.

These results represented a significant improvement in the recognition of models for myoelectric control systems in terms of real-time performance, with a small number of input channels, and an important step towards the implementation of an intuitive multifunctional controller and propelled research in the field of control strategies of myoelectric systems based on model recognition (Hargrove et al., 2007).

In recent years, an intense effort has been made to investigate the effects of feature sets and classifiers on the classification accuracy of EMG signal recognition. The function sets consisting of TD statistics, autoregressive coefficients (AR) and information from time-frequency statistics were used to help classify the EMG signal measured in both continuous contractions and transient shocks.

Artificial neural networks, genetic algorithms, Bayes classifiers, Gaussian mixture models (GMM) and fuzzy logic have proven to be classifiers with acceptable performance. It has also been shown that for these combinations of feature sets and classifiers, classification accuracy is affected more by the choice of feature set than by the choice of classifier.

The main components of a myoelectric controller based on signal shape recognition are shown in Figure 1.

Certain specific components that have been shown to provide good classification accuracy using the information extracted from the surface EMG signal are highlighted (Hargrove et al., 2007).

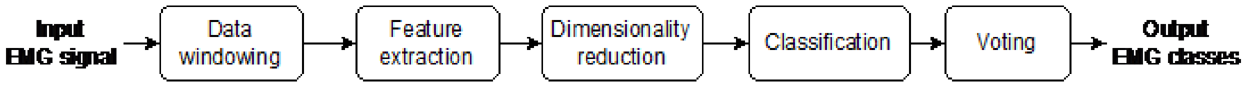

***Fig. 1:** Electromyographic signal analysis components [reproduction after (Hargrove et al., 2007)]*

Data window

A data window is used for analysis because the instantaneous value of the MES is not suitable for the control of myoelectric devices. However, it has been suggested that a user will notice an annoying difference if there is a delay in perception of more than 300 ms. Consequently, the analysis window plus the associated processing delay must be less than 300 ms.

Extraction of signal characteristics

In the context of classifying the EMG model, extracting the characteristics of the signal is the activity of extracting useful information from the signal and to be used to make the sets of characteristics that are used by the classifier. Character selection generally reduces the dimensionality of the classification problem by replacing the discrete signal with a feature vector, which contains specific representations. However, choosing a feature set that is representative of the data is not easy. In fact, selecting a suitable feature set is the most difficult task of classifying models.

Dimensionality reduction

Depending on the nature of a classification problem, size reduction may be necessary to obtain acceptable classification accuracy. Given a multivariate data set (feature set), the role of dimensionality reduction is to find a smaller set of variables (features) with low redundancy, which would provide a better representation of the original data. A classifier with fewer inputs has fewer parameters to be determined, which leads to a better generalization function. One method of dimensional reduction that has been shown to work well for myoelectric control is principal component analysis (PCA).

Classification of models

The signal classification attempts to associate the measured data with a limited number of output classes. There are three distinct approaches to model classification: 1) the statistical approach, 2) the structural approach, and 3) the machine learning approach.

The statistical approach classifies the data using an estimate of the probability density function in an N-dimensional space and tries to divide the space into a region for each class based on the probability density functions.

The structural approach uses structural information to segment the signal into primitives and then performs the classification based on the sequence of determined primitives. Most learning approaches use a neural network to learn the data structure for each class. Of these three approaches, the statistical and learning approaches were the most used for myoelectric control based on model recognition.

A classifier based on linear discriminant analysis (LDA) can be a representative example for the statistical classifier, while a multilayer perceptual artificial neural network (MLP) will be used as a representative example of a neural classifier; both have been shown to provide high classification accuracy in the control of myoelectric devices based on signal recognition.

Weighting of classifiers

Ideally, the classifier will choose the desired output for each vector of input characteristics, but for various reasons the classifier sometimes misclassifies a particular signal. A majority voting scheme can be used to correct a small number of classifications and to improve the overall accuracy of the control system classification (Hargrove et al., 2007).

Another method of advanced EMG signal analysis employs a convolutional neural network architecture for the recognition of neuromuscular activity based on images generated using the instantaneous values of High-Density recordings made for the sEMG surface electromyographic signal.

In general, the approach based on the use of High Density (HD-sEMG) images includes the use of classical convolutional neural networks (ConvNet) that require extensive computational resources for training. Pre-trained networks are usually used on the basis of very large data sets, but these are computationally prohibitive.

In this regard, De Venuto et al. (2015) propose a simplified architecture for the convolutional neural network, called S-ConvNet, which is very effective in learning the classification of HD-sEMG images for the recognition of neuromuscular activity. This does not require the use of pre-trained models, and the data set on which the training is performed is small in size. The performances obtained are comparable to the best results in the field, and this method can be used much more easily in scenarios where there are constraints on available resources.

Recognition of neuromuscular activity is very important for many applications that have an impact on daily life. Most applications are in the field of non-invasive control of prosthetic devices, but there may be other examples, such as methods of interaction with video games or the diagnosis of neuromuscular disorders.

Conventional approaches for recognizing neuromuscular activity are mainly based on the use of multi-channel sensors for recording surface electromyographic signal (sEMG), but they have serious limitations due to electrode movement, and disturbances within a channel can affect the performance of the entire system.

For this reason, methods based on the use of high-density surface electromyographic signal (HD-sEMG) are preferred. For this, a two-dimensional (2D) structure of electrodes is used that records the sEMG signal so that the spatial distribution of the myoelectric activity can be achieved for the muscles located in the area where the electrodes were placed.

HD-sEMG data are spatially correlated, unaffected by disturbances that may occur on the communication channel. Still, however, current methods of analyzing the neuromuscular activity of the HD-sEMG signal require the use of a time window for segmentation, which involves identifying the optimal parameters for its configuration, which may affect the accuracy of the classification. Delays in data transmission can also be introduced, which can disrupt some applications in areas such as assistive technologies or the human-computer interface.

To overcome these drawbacks, various solutions have been investigated that try to improve the way the analysis is performed using only instantaneous values of the sEMG signal. In this situation, the measured values are distributed in a two-dimensional matrix according to the position of the electrodes in the device with sEMG sensors. After that, the numerical data is converted into values that represent the intensity of the gray tones to generate an sEMG image.

Based on these images, various classical classification methods can be applied, such as SVM or ConvNet-type neural networks, and a very good performance is obtained in the case of recognition of neuromuscular activity.

The disadvantage of these methods based on convolutional neural networks is the need to have large data sets for training, as well as significant computational resources.

Other methods and techniques for EMG signal analysis using the Wavelet and Fourier transform, neural networks, and SVM classifiers have been investigated by Englehart, Hudgins & Parker (2001), Huang, Englehart, Hudgins & Chan (2005), Lucas, Gaufriau, Pascual, Doncarli, & Farina (2008), Nazarpour, Sharafat & P. Firoozabadi (2005), Oskoei & Hu (2008) and Sparto, Parnianpour, Barria & Jagadeesh (2000).

APPLICATIONS OF ELECTROMYOGRAPY

Motion Prediction

The paper of Tortora, Michieletto, Stival, & Menegatti (2019) investigates a way to improve the prediction of a person's movement during activities that require human-robot collaboration in industrial installations, as better human-machine collaboration is necessary for specific areas and work settings. Therefore, especially for robots that interact with a person, it is essential that they can understand the human movement to avoid accidents. The proposed solution can have many applications in the field of Industry 4.0, where autonomous robots are an essential component in innovative enterprises. The ability to predict motion intention as well as the prediction of direction of motion are necessary and need to be optimized to improve the speed and accuracy of human motion detection. The output of the two predictors was used as an external input for a finite automaton (FSM) that was implemented to control the behavior of a robot depending on the action or inaction of the user.

Discrimination of gestures made by one person is an extremely important element for the development of solutions to assist people who need neurorehabilitation, are elderly or have various health problems that make them dependent on another person to continue their work at a normal level.

An application development framework for mobile devices that analyzes the electromyographic signal (EMG) as an auxiliary component in physiotherapy sessions or for prosthesis calibration is investigated by Ceolini, Taverni, Khacef, Payvand, & Donati (2019). This framework allows the integration of data from multiple sensors and visual information with the EMG signal, in order to improve the accuracy of gesture recognition.

Monitoring Eating Behavior

(Nicholls et al., 2019) have developed an automatic system for detecting eating behavior using electromyographic sensors (EMG). They also investigated the application of such a system together with haptic feedback, in real time, by means of a band placed on the arm, to support a balanced diet.

The study used data collected from 16 participants, and a model was developed for detecting chewing and swallowing, using 18 characteristics of the EMG signal that were extracted and then analyzed with various classical classifiers.

Based on this model, a system was developed to allow participants to self-moderate their chewing behavior using tactile feedback received from the armband.

In addition, an additional experimental study was conducted with 20 participants that showed that subjects had a lower chewing rate when tactile feedback was activated in the form of a vibration produced by the armpit, compared to the initial situation and condition without haptic feedback.

Control of Hand Orthosis

People use their hands to perform various activities like handling objects, manipulating tools, or simply gesturing. The loss of a hand can cause severe trauma, as it is an important human body part. More than 50000 people in Europe have an upper limb amputated, whereas in the United States, this number is over 40000 people, and the WHO projects that approximately 40 million people in the world are in this situation and that this number will continue to increase.

For people with an amputated upper limb, the use of a practical prosthetic hand can improve the quality of life in a significant manner. These devices need to have a very robust control system, and although several methods have been proposed for the control of hand orthosis, there is a significant gap between the planned and implemented functionalities, which makes this an open issue.

For example, there are several ways to control a prosthetic device, using keyboards and joysticks, voice recognition technology, or other biomedical signals such as EEG or EMG. Of these modes, the use of an electromyographic signal is one of the most convenient methods for a person with an amputated limb.

The prosthetic devices that use the electromyographic signal for control purposes use sensors that can be implanted directly into the muscles, such as intramuscular EMG (imEMG) or sensors that are inserted directly into the skin - surface EMG (sEMG). Even though the intramuscular sensors are more accurate and provide a better signal-to-noise ratio, they are intrusive and difficult to use, which makes this type of sensors not very practical. Instead, the surface sEMG sensors which use wet or dry skin contact are more convenient to use (wet contact sensors use a gel which might be inconvenient for a person with an amputated limb, but they are more accurate).

There are a couple of ways to control a hand prosthetic device using EMG signals. The first way is to quantify the average absolute value of EMG signals and then use a finite automaton to determine a state under which the device should be operated. This method is the simplest and provides a robust way to control a device using the EMG signal, however the prosthetic hand is limited to a few basic movements.

The other way is to use machine learning algorithms to classify EMG signals and then to convert the estimated response into a command. This method usually includes all of the standard steps of pattern matching algorithms, such as pre-processing, extracting features, reducing the size of the samples, and then using a classifier and a search table.

Jafarzadeh et al. (2019) developed a control system for prosthetic hands based on EMG electromyographic signal analysis. The proposed system uses a series of 8 EMG electrodes evenly spaced. Several types of convolutional neural networks (CNN) have been investigated, and the best architecture which was selected uses raw EMG signals without pre-processing and feature extraction. A post-processing subsystem that includes both an input memory and an aggregation unit has been introduced to improve the accuracy. The main advantage of this method compared with traditional ones is that instead of several pre-processing steps and feature extraction, only a new convolutional neural network is used to analyze the electromyographic signal.

Emotion recognition

There are several classification systems for emotions, which can be of eight basic types: anger, fear, sadness, disgust, surprise, anticipation, acceptance, and joy, with all other types to be formed by combining these basic ones.

The paper of Rashid et al. (2019) analyzes the electromyographic signals recorded using the MyoSensor sensor (MyoSensor, n.d.) which are classified into two classes - relaxed and nervous. To achieve this classification, a data set was created based on data collected from

10 users, by extracting 8 significant features that were used together with an SVM classifier.

The EMG signal recorded on the forearm can be used to determine a person's emotional state, with experimental results showing an accuracy of 88.1% after 300 iterations.

DISCUSSION

As it was presented in the previous sections, there is a vast amount of research concerning electromyographic signal analysis and applications. The diversity of use cases for electromyography represents a critical aspect that underscores the utility of biomedical signals. Especially with regard to the study of emotional state and human behavior, it is pertinent to consider their impact on other domains.

For example, the implications from the cybersecurity perspective are notable, considering that the human factor is the weakest link of the security chain. To this end, it is salient to discuss the phishing attack from an emotional perspective and to consider the support that electromyography can provide in this context.

Phishing is a critical risk to any person and organization, and researchers have carried out numerous studies to identify the factors that determine this threat and influence users' susceptibility to phishing campaigns. Phishing is the act of deceitfully contacting a person to make the person perform something harmful. This kind of incident occurs by email, typically when a user receives an email from a familiar address requesting private or confidential information or performing a specific malicious task.

Phishing susceptibility represents the probability that a person performs the request sent via a fraudulent message. This type of attack is more straightforward than other kinds of attacks that circumvent firewalls and other protection systems. Also, the attack can be repeated and targeted on different users, increasing the likelihood that some persons will eventually be tricked and fall for the scam. In addition, many users are prone to trust the medium and thus perform the tasks requested (Sommestad & Karlzen, 2019).

Phishing is also a social engineering deception that aims to produce both financial and personal harm to people and organizations. The influence of human behavior and emotions on people's security related actions have been studied in depth, including the effects of the COVID-19 outbreak on human emotions and its impact on phishing success (Abroshan et al., 2021a, 2021b). For instance, the fear of COVID-19 influences the success of COVID-19 specific themed phishing scams, while anxiety, stress, and risk-taking impact on the success of both the COVID-19 themed and common phishing attacks.

In (Chen et al., 2020) it is shown that an individual's phishing susceptibility could be influenced by recent phishing encounters, and Parker & Flowerday (2020) conclude that certain people are more susceptible to phishing attacks due to their online habits, demographic factors, technical knowledge, and personality traits. For example, young women with low technical and security knowledge who use social media for an extended period are a high-risk category of people susceptible to phishing attacks.

Exploring phishing susceptibility from an emotional perspective has been performed by Tian & Jensen (2019) and LeFranc & Savoli (2019), as research shows that emotions play an essential role in people's decision-making process. They argue that employees' emotional attachment and commitment to the organization and their perception of the urgency of the email can produce both positive and negative emotions, which can influence the susceptibility to phishing attacks.

Therefore, the proposition set forth is that electromyography could be a helpful instrument in analyzing the emotional state, among other domains, and particularly from the cybersecurity perspective, the phishing susceptibility could be better understood and mitigated.

CONCLUSIONS

This study was dedicated to the analysis of the electromyographic signal produced by the contraction of muscle fibers. Its main characteristics were presented, together with the primary analysis techniques based on statistical methods and deep neural networks. Several applications of electromyographic signal analysis were also described, including motion prediction, monitoring eating behavior, or controlling a hand orthosis.

The EMG is a biomedical signal and can be used to detect a disease or rehabilitate a person with the help of an artificial limb. However, a particular application of electromyography is emotion recognition. This feature is helpful in analyzing phishing susceptibility as the emotional state has been shown to influence human behavior.

AKNOWLEDGEMENTS

The present work has been supported by the PN 102 Core project - “Cybernetic polygon for industrial control systems (ROCYRAN)” and PN 301 Core project - “Non-invasive monitoring and health assessment system in a smart environment for the elderly (Ro-SmartAgeing)”.

REFERENCE LIST

Abroshan, H., Devos, J., Poels, G. & Laermans, E. (2021a). COVID-19 and Phishing: Effects of Human Emotions, Behavior, and Demographics on the Success of Phishing Attempts During the Pandemic. *IEEE Access, 9*, 121916-121929. https://doi.org/10.1109/ACCESS.2021.3109091

Abroshan, H., Devos, J., Poels, G. & Laermans, E. (2021b). A phishing Mitigation Solution using Human Behaviour and Emotions that Influence the Success of Phishing Attacks. *Adjunct Proceedings of the 29th ACM Conference on User Modeling, Adaptation and Personalization*, 345-350. https://doi.org/10.1145/3450614.3464472

Ceolini, E., Taverni, G., Khacef, L., Payvand, M. & Donati, E. (2019). Sensor fusion using EMG and vision for hand gesture classification in mobile applications. *ArXiv*. https://arxiv.org/abs/1910.11126

Chen, R., Gaia, J. & Rao, H. R. (2020). An examination of the effect of recent phishing encounters on phishing susceptibility. *Decision Support Systems*, 133, 113287. https://doi.org/10.1016/j.dss.2020.113287

De Venuto, D., Annese, V. F., de Tommaso, M., Vecchio, E., & Sangiovanni Vincentelli, A. L. (2015). Combining EEG and EMG signals in a wireless system for preventing fall in neurodegenerative diseases. In B. Andò, P. Siciliano, V. Marletta, & A. Monteriù (Eds.), *Ambient Assisted Living* (Vol. 11, pp. 317-327). Cham: Springer International Publishing. doi:10.1007/978-3-319-18374-9_30

Englehart, K., Hudgins, B. & Parker, P. A. (2001). A wavelet-based continuous classification scheme for multifunction myoelectric control. *IEEE Transactions on Bio-Medical Engineering*, *48*(3), 302-311. doi:10.1109/10.914793

Faust, O., Hagiwara, Y., Hong, T.J., Lih, O.S. and Acharya, U.R. (2018). Deep learning for healthcare applications based on physiological signals: A review. *Computer Methods and Programs in Biomedicine, 161*, 1-13.

Hargrove, L. J., Englehart, K. & Hudgins, B. (2007). A comparison of surface and intramuscular myoelectric signal classification. *IEEE Transactions on Bio-Medical Engineering, 54*(5), 847-853.

Huang, Y., Englehart, K. B., Hudgins, B. & Chan, A. D. C. (2005). A Gaussian mixture model based classification scheme for myoelectric control of powered upper limb prostheses. *IEEE Transactions on Bio-Medical Engineering, 52*(11), 1801-1811. doi:10.1109/TBME.2005.856295

Hudgins, B., Parker, P. & Scott, R. N. (1993). A new strategy for multifunction myoelectric control. *IEEE Transactions on Bio-Medical Engineering 40*(1), 82-94.

Jafarzadeh, M., Hussey, D. C. & Tadesse, Y. (2019). Deep learning approach to control of prosthetic hands with electromyography signals. *ArXiv*. https://arxiv.org/abs/1909.09910

LeFranc, N. & Savoli, A. (2019). Factors Influencing Employees’ susceptibility to Phishing Emails: The Role of Emotions. *The 13th Mediterranean Conference on Information Systems (MCIS)*, Naples, Italy.

Lucas, M.-F., Gaufriau, A., Pascual, S., Doncarli, C. & Farina, D. (2008). Multi-channel surface EMG classification using support vector machines and signal-based wavelet optimization. *Biomedical Signal Processing and Control, 3*(2), 169-174. doi:10.1016/j.bspc.2007.09.002

MyoSensor. (n.d.). About MyoSensor. Retrieved October 10, 2021, from https://myosensor.eeecs.qub.ac.uk

Nazarpour, K., Sharafat, A. & P Firoozabadi, S. (2005). Surface EMG signal classification using a selective mix of higher order statistics. *Conference Proceedings: Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 4*, 4208-4211. doi:10.1109/IEMBS.2005.1615392

Nicholls, B., Ang, C. S., Kanjo, E., Siriaraya, P., Yeo, W.-H., & Tsanas, A. (2019). An EMG-based Eating Behaviour Monitoring System with Haptic Feedback to Promote Mindful Eating. *ArXiv*.

Oskoei, M. A. & Hu, H. (2008). Support vector machine-based classification scheme for myoelectric control applied to upper limb. *IEEE Transactions on Bio-Medical Engineering, 55*(8), 1956-1965. doi:10.1109/TBME.2008.919734

Parker, H. J. & Flowerday, S. V. (2020). Contributing factors to increased susceptibility to social media phishing attacks. SA Journal of Information Management, 22(1). https://doi.org/10.4102/sajim.v22i1.1176

Raqeeb Technology Blog. (n.d.). Myoelectric Voltages. Retrieved October 10, 2021, from https://rqbsk.wordpress.com/2019/04/12/myoelectric-voltages

Sparto, P. J., Parnianpour, M., Barria, E. A. & Jagadeesh, J. M. (2000). Wavelet and short-time Fourier transform analysis of electromyography for detection of back muscle fatigue. *IEEE Transactions on Rehabilitation Engineering, 8*(3), 433-436. doi:10.1109/86.867887

Rashid, M. S., Zaman, Z., Mahmud, H. & Hasan, M. K. (2019). Emotion Recognition with Forearm-based Electromyography. ArXiv. https://arxiv.org/abs/1911.05305

Sommestad, T., & Karlzen, H. (2019). A meta-analysis of field experiments on phishing susceptibility. 2019 APWG Symposium on Electronic Crime Research (ECrime), 1-14. https://doi.org/10.1109/eCrime47957.2019.9037502

Tian, C. A. & Jensen, M. L. (2019). Effects of emotional appeals on phishing susceptibility. *Proceedings of the 14th Pre-ICIS Workshop on Information Security and Privacy*.

Tortora, S., Michieletto, S., Stival, F. & Menegatti, E. (2019). Fast human motion prediction for human-robot collaboration with wearable interfaces. *ArXiv*. https://arxiv.org/abs/1905.11734