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Artikel Jurnal Internasional Bereputasi:
Sudut Pandang Reviewer

Ir. Khairul Anam, S.T., M.T., PhD
Universitas Jember

Short CV (Publons)

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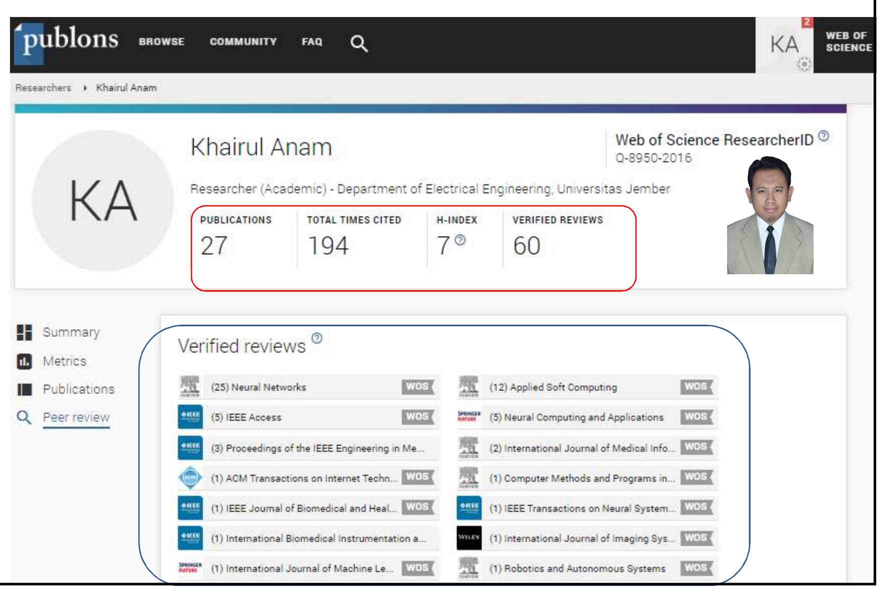
Your impact over time



AREA OF INTEREST
Bio-signal pattern recognition
Intelligent control system and Robotics
Applied Machine Learning

Rekap review di Publons(WoS)

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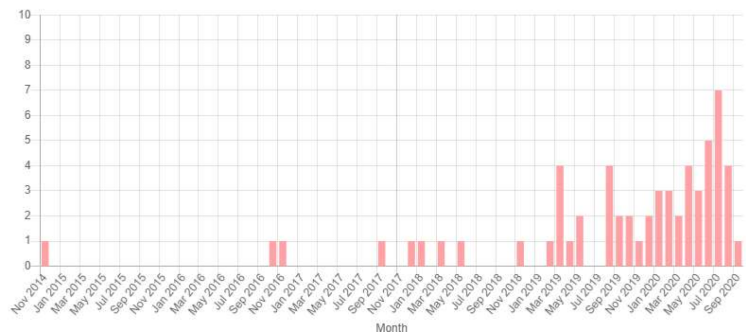
VERIFIED REVIEWS	VERIFIED REVIEWS (LAST 12 MONTHS)	REVIEW TO PUBLICATION RATIO
60	37	2.2:1
Median: 3 97th percentile	Median: 1 99th percentile	Median: 0.3:1

Reviews per month

Month



Aktifitas Reviewer Terverifikasi di Wos

publons BROWSE COMMUNITY FAQ KA WEB OF SCIENCE

Researchers

Web of Science Core Collection only · Last 12 months · Highly Cited Researchers · Peer review award winners

Last updated 1 hour, 35 minutes ago

#	RESEARCHERS	INSTITUTION	# PUBLICATIONS	# VERIFIED REVIEWS	# VERIFIED EDITOR RECORDS
1	Jonas Ranstam	Lund University	274	5,987	-
2	Timothy T Houle	Harvard Medical School	175	4,405	-
3	Lingxin Chen	Chinese Academy of Sciences	335	3,221	162
4	Seyedali Mirjalili	Torrens University Australia	145	2,848	143
5	Andrej M. Kielbassa	Danube Private University	171	2,224	237
6	Mohammad Mehdi Rashidi	Tongji University	289	1,976	199
7	Ahmed Abdel Razek	Mansoura University	107	1,917	8
8	Wei-Chiang Hong	Oriental Institute of Technology	94	1,915	366
9	Swapnil Fegade	University of North Dakota Grand Forks	15	1,892	3
10	Gaetano Santulli	Columbia University	195	1,811	5
11	KC Kwok-wing Chau	Hong Kong Polytechnic University	212	1,675	488

Aktifitas Reviewer Terverifikasi di Wos (12 bulan terakhir)

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publons BROWSE COMMUNITY FAQ KA WEB OF SCIENCE

Researchers

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- [ ] Highly Cited Researchers
- [ ] Peer review award winners

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#	RESEARCHERS	INSTITUTION	# PUBLICATIONS	# VERIFIED REVIEWS	# VERIFIED EDITOR RECORDS
1	Seyedali Mirjalili	Torrens University Australia	26	1,490	36
2	Lingxin Chen	Chinese Academy of Sciences	3	817	2
3	Ahmed Abdel Razek	Mansoura University	-	809	-
4	Babak Mohammadi	China Institute of Water Resources and Hydrop...	7	743	2
5	Indranil Saha	IQ City Medical College and Narayana Hrudayal...	-	618	65
6	Wei-Chiang Hong	Oriental Institute of Technology	10	611	23
7	Xinghua Li	Wuhan University	1	604	-
8	Yang Li	Argonne National Laboratory	-	598	65
9	Kwok-wing Chau	Hong Kong Polytechnic University	-	575	19
10	Jonas Ranstam	Lund University	-	540	-
11	Pau-Loke Show	University of Nottingham	73	529	40

Aktifitas Reviewer Terverifikasi di Wos

INDONESIA

publons BROWSE COMMUNITY FAQ KA WEB OF SCIENCE

Researchers

METRICS DISPLAY

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- [ ] Last 12 months

AWARDS

- [ ] Highly Cited Researchers
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Limited to 250 of 14,340 results

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#	RESEARCHERS	INSTITUTION	# PUBLICATIONS	# VERIFIED REVIEWS	# VERIFIED EDITOR RECORDS
1	Suryadi Ismadji	Widya Mandala Catholic University Surabaya	170	820	-
2	Leny Yuliati	Universitas Ma Chung	86	207	8
3	Anne Marie Kuijpers-Jagtman	University Medical Center Groningen (UMCG), U...	341	190	174
4	Doddy Prayogo	Universitas Kristen Petra	17	189	1
5	Eddy Heraldy	Universitas Sebelas Maret	26	170	-
6	Hadi Nur	Universiti Teknologi Malaysia	147	137	31
7	Is Fatimah	Universitas Islam Indonesia	81	109	-
8	Achmad Nizar Hidayanto	University of Indonesia	126	108	-
9	Arridina Susan Silitonga	State Polytechnic of Medan	45	100	-
10	Tjandra Setiadi	Institut Teknologi Bandung (ITB)	27	100	-

Aktifitas Reviewer Terverifikasi di Wos

INDONESIA
12 bulan
terakhir

publons BROWSE COMMUNITY FAQ KA WEB OF SCIENCE

Researchers

METRICS DISPLAY: Web of Science Core Collection only; Last 12 months
AWARDS: Highly Cited Researchers; Peer review award winners

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#	RESEARCHERS	INSTITUTION	# PUBLICATIONS	# VERIFIED REVIEWS	# VERIFIED EDITOR RECORDS
1	SI Suryadi Ismadji	Widya Mandala Catholic University Surabaya	9	130	-
2	RP Raymond Pranata	Universitas Pelita Harapan	42	85	-
3	Is Fatimah	Universitas Islam Indonesia	7	65	-
4	Gunadi	Faculty of Medicine, Public Health, and Nursing...	-	60	-
5	Arridina Susan Silitonga	State Polytechnic of Medan	1	47	-
6	Asra Al Fauzi	Airlangga University	-	42	-
7	AH Achmad Nizar Hidayanto	University of Indonesia	13	41	-
8	Yehezkiel Steven Kurniawan	Universitas Ma Chung	4	40	-
9	Diah Harnoni Apriyanti	Indonesian institute of sciences (LIPI)	-	38	-
10	KA Khairul Anam	Universitas Jember	-	37	-

Aktifitas Reviewer Terverifikasi di Wos

Universitas Jember

publons BROWSE COMMUNITY FAQ KA WEB OF SCIENCE

Researchers

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65 results — *Last updated 1 hour, 45 minutes ago*

#	RESEARCHERS	INSTITUTION	# PUBLICATIONS	# VERIFIED REVIEWS	# VERIFIED EDITOR RECORDS
1	Bambang Kuswandi	Universitas Jember	-	63	-
2	KA Khairul Anam	Universitas Jember	20	56	-
3	Tantut Susanto	Universitas Jember	16	12	-
4	Fahmi Arif Kurnianto	Universitas Jember	6	8	-
5	Abubakar Eby Hara	Universitas Jember	4	4	-
6	AT Agus Trihartono	Jember University Centre for Research in Social...	7	2	-
7	RH Rifati Handayani	Universitas Jember	1	1	-
8	BS Bambang Sujanarko	Universitas Jember	-	1	-
9	Mochamad Asrofi	Universitas Jember	9	1	-
10	HP Hari Purnomo	Universitas Jember	-	1	-
11	indarto indarto	-	3	1	-
12	Slamin	Universitas Jember	-	1	-
13	BS Budi Setyono	Universitas Jember	-	1	-

Keuntungan sebagai Reviewer Internasional Bereputasi

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- Amal sholeh bekal akherat
- Aknowledgment
- Terkadang diberi akses free ke publisher
- Memenuhi syarat lompat jabatan

PO PAK 2019+REVISINYA

3.1. UNTUK SETIAP YANG NAIK KE PROFESOR

(1) Tambahan syarat khusus selain karil syarat khusus untuk usulan ke GURU BESAR/PROFESOR

Undang–Undang Nomor 14 Tahun 2005 Tentang Guru dan Dosen Pasal 49: Profesor merupakan jabatan akademik tertinggi yang mempunyai kewenangan membimbing calon doktor, maka selain persyaratan karya ilmiah untuk pemenuhan persyaratan khusus, untuk pengajuan usulan profesor juga dipersyaratkan:

(1) Pernah mendapatkan hibah penelitian kompetitif/penugasan tingkat daerah/nasional/ kementerian/ internasional/korporasi, atau kompetitif internal Perguruan Tinggi, (sebagai ketua, kecuali penelitian program tesis/disertasi); atau

(2) Pernah membimbing/membantu membimbing program doktor, atau

(3) Pernah menguji sekurang-kurangnya tiga mahasiswa program doctor (baik di perguruan tinggi sendiri maupun perguruan tinggi lain); atau

(4) Sebagai reviewer sekurang-kurangnya pada 2 (dua) jurnal internasional bereputasi yang berbeda.

DISCLAIMER

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- Materi dalam presentasi ini berdasarkan pengalaman kami sendiri
- Ada beberapa materi berhak cipta, diinformasikan di bagian bawah halaman. Mohon bijak dalam menggunakannya.

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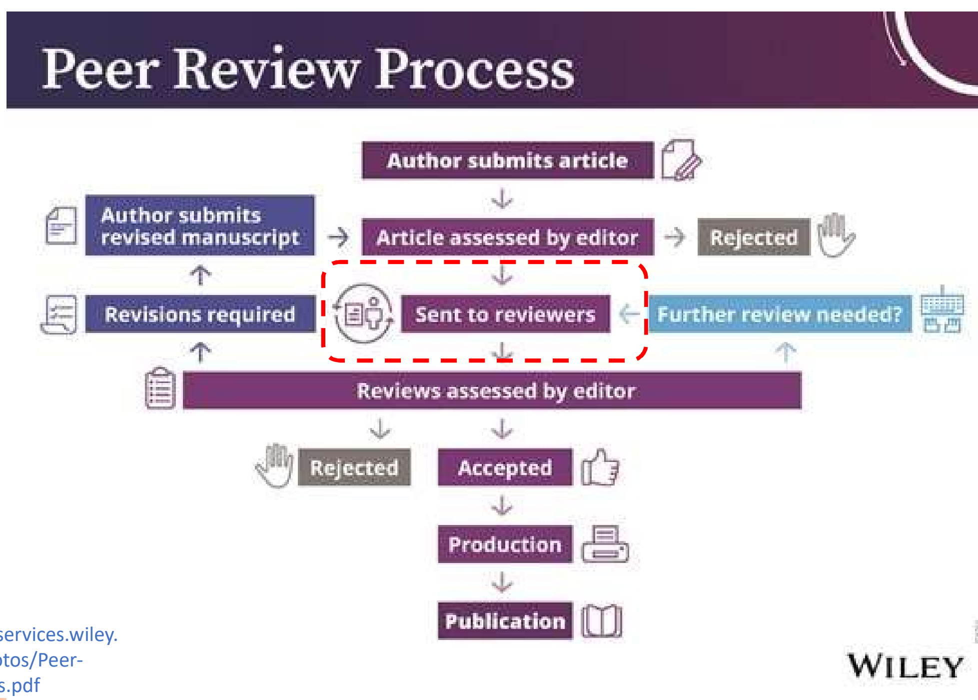
PERAN REVIEWER



https://authorservices.wiley.com/asset/photos/Peer-Review-Process.pdf

Tugas Reviewer

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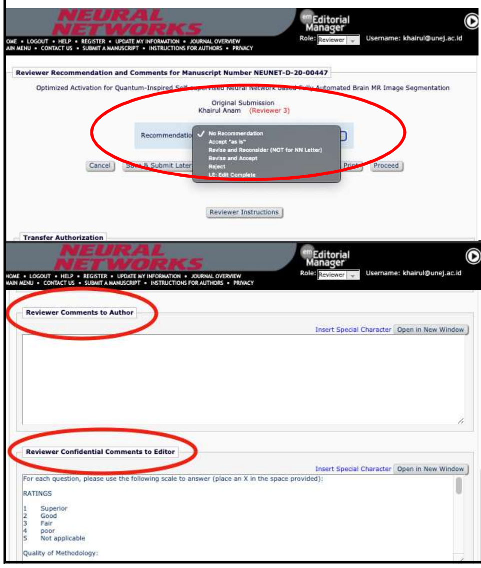
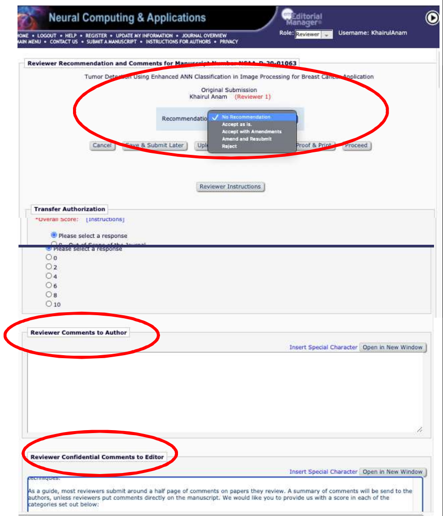


Memberi Rekomendasi

Komentar untuk PENULIS

Komentar untuk EDITOR



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Apa yang dicari Reviewer?

Originalty

- Apakah karya asli dan apakah memberikan kontribusi lebih lanjut terhadap apa yang sudah ada dalam literatur yang diterbitkan?

Quality

- Apakah pertanyaan atau hipotesis penelitian didefinisikan dengan jelas dan dijawab dengan tepat? Apakah keseluruhan desain penelitian ini memadai? Apakah klaim penulis dapat diterima?

Quantity

- Apakah data cukup? Apakah penulis perlu melakukan eksperimen lebih lanjut untuk mendukung klaim mereka?

Readability

- Apakah ada terlalu banyak informasi yang tidak berguna yang disajikan yang mengaburkan poin utama? Apakah ada cara untuk memperbaikinya?

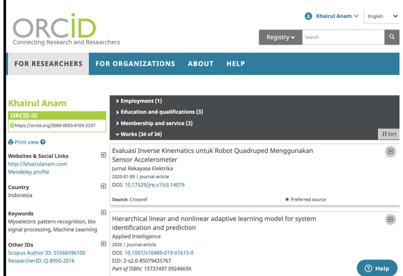
IN GENERAL: Mencari jawaban dari pertanyaan-pertanyaan ini

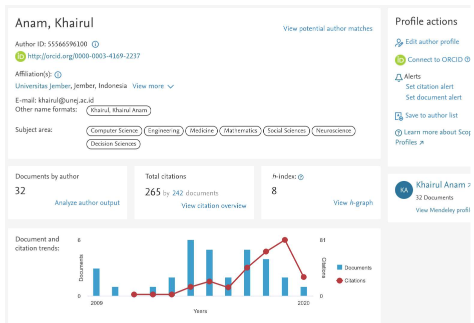
Peer-Review Techniques for Novices
By Lesley McKarney

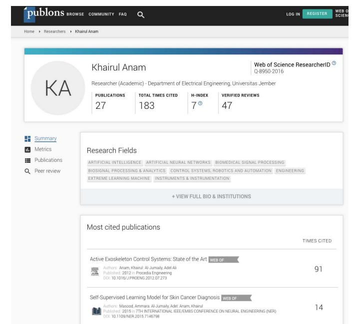
IN DETAIL: MEMERIKSA SEMUA BAGIAN DARI ARTIKEL

- The author profile (optional)
- Abstract and keywords
- INTRODUCTION
- MATERIALS AND METHODS
- RESULTS AND DISCUSSION (CONCLUSION)
- REFERENCES

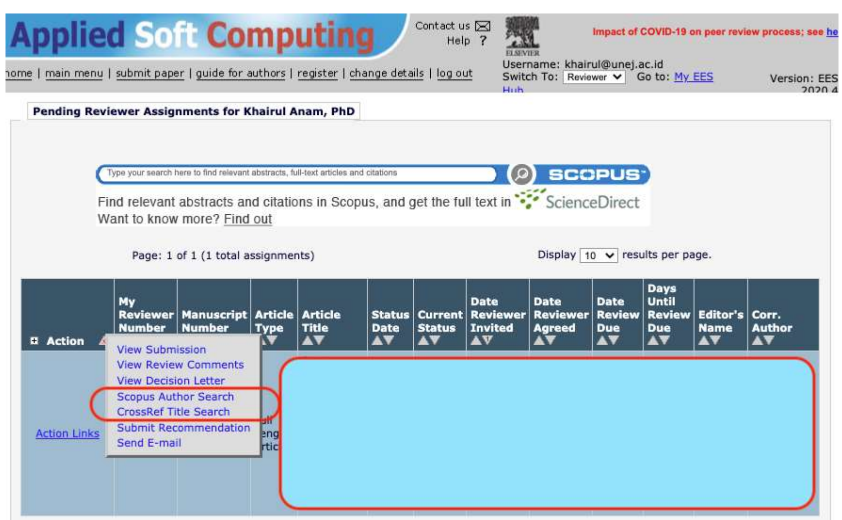
AUTHOR PUBLICATION PROFILE (OPTIONAL)







AUTHOR PUBLICATION PROFILE (Cont'd)



Abstrak dan Kata Kunci

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ABSTRACT	KEYWORDS
• Abstrak MELAPORKAN hipotesis, metode, dan hasil • Ringkas, teknis dan informatif. • Menyajikan pernyataan masalah, tujuan, metodologi yang jelas, hasil dan diskusi singkat	• Kata kunci sebaiknya TIDAK sama persis dengan judulnya. • Mewakili item pencarian tambahan yang meningkatkan visibilitas artikel dan memudahkan dicari oleh Search Engine

Evaluation of feature extraction techniques and classifiers for finger movement recognition using surface electromyography signal

Pornchai Phukpattaranont[1] · Sirinee Thongpanja[1] · Khairul Anam[2] · Adel Al-Jumaily[2] · Chusak Limsakul[1]

Received: 13 December 2017 / Accepted: 27 May 2018

EXAMPLE #1

Abstract

Background

Electromyography (EMG) in a bio-driven system is used as a control signal, for driving a hand prosthesis or other wearable assistive devices. Processing to get informative drive signals involves three main modules: preprocessing, dimensionality reduction, and classification. This paper proposes a system for classifying a six-channel EMG signal from 14 finger movements. Objective A feature vector of 66 elements was determined from the six-channel EMG signal for each finger movement. Subsequently, various feature extraction techniques and classifiers were tested and evaluated. We compared the performance of six feature extraction techniques, namely principal component analysis (PCA), linear discriminant analysis (LDA), uncorrelated linear discriminant analysis (ULDA), orthogonal fuzzy neighborhood discriminant analysis (OFNDA), spectral regression linear discriminant analysis (SRLDA), and spectral regression extreme learning machine (SRELM). In addition, we also evaluated the performance of seven classifiers consisting of support vector machine (SVM), linear classifier (LC), naive Bayes (NB), *k*-nearest neighbors (KNN), radial basis function extreme learning machine (RBF-ELM), adaptive wavelet extreme learning machine (AW-ELM), and neural network (NN). Method The results showed that the combination of SRELM as the feature extraction technique and NN as the classifier yielded the best classification accuracy of 99%, which was significantly higher than those from the other combinations tested.

mian result and short discussion

Keywords Electromyography (EMG) · Feature extraction · Dimensionality reduction · Finger movement classification · EMG pattern recognition

EXAMPLE #2

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[redacted] the training. In the online experiments, using 10-trained classes, the MCS achieved an accuracy of 89.73 % and 89.22 % using RBF-ELM-R and RBF-ELM, respectively. In the experiment with 5-trained classes and 5-untrained classes, the MCS attained the accuracy of 80.22 % and 59.64 % using RBF-ELM-R and RBF-ELM, respectively.

REVIEWER'S COMMENTS

Abstrak (P. 1): Akan lebih disukai jika abstrak menyertakan beberapa indikasi interpretasi dan kesimpulan penulis.

EXAMPLE #3

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Abstract— **The classification accuracy of a pattern recognition is mostly determined by the extracted features and the utilized classifiers. However, the feature is more dominant than the classifiers. Many efforts have been conducted to obtain the best features either by introducing a new feature or proposing a new projection method to increase class separability. Recently, spectral regression extreme learning machine (SRELM) has been introduced to improve the class separability of the features. However, the evaluation was only focused on the myoelectric or electromyography pattern recognition using many EMG channels. The performance of SRELM for fewer EMG channels has not been evaluated. This paper examined the performance of SRELM for bio-signal pattern recognition using two EMG channels. The experimental results show that SRELM performed well when dealing with different class numbers by classification accuracy of around 95.67% for 10 class movements across eight subjects. Furthermore, SRELM is better than spectral regression discriminant analysis (SRDA). In fact, both, SRELM and SRDA use same methods, spectral regression, in the process.**[11]

REVIEWER'S COMMENT:
Abstrak terdiri dari 220-250 kata, menjelaskan rumusan masalah, tujuan, metodologi yang jelas, hasil dan pembahasan singkat

INTRODUCTION

- Apakah pendahuluan menyajikan alasan yang jelas dan eksplisit mengapa penelitian dilakukan?
- Apakah pendahuluan mengacu pada studi penting sebelumnya di bidangnya (referensi yang berlebihan harus dihindari) → "tinjauan literatur singkat"
- Tinjauan literatur (literatur review) berisi:
  - Apa yang diketahui
  - Apa yang tidak diketahui
  - Bagaimana artikel kita mengisi celah/gap
  - Tinjauan pustaka harus memadai, baru, dan relevan, dan dapat memberi tahu pembaca posisi penelitian dalam lingkup bidang ilmu
  - Alur tinjauan literatur mengalir halus
- Apakah pendahuluan berisi hipotesis eksplisit atau tujuan penelitian atau pertanyaan penelitian?
- Apakah hasil dan pembahasan berhubungan dengan hipotesis yang disajikan dalam pendahuluan?

EXAMPLE #1

1. Introduction

A hand disability is one c
that occur in the communit
either amputation or a mot
of the perfect technology f
task. Various cutting-edge
deal with the hand rehal
Bionics Limited has introd
named iLimb (TouchBionic
hand, and it is designed in s
shape of an object being g

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Technology, Sydney, Building 11 R
Australia.
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http://dx.doi.org/10.1016/j.neune
0893-6080/© 2016 Elsevier Ltd. A

processed fast Fourier transform (FFT) features extracted from two electromyography (EMG) channels. Using this system, they could classify five-finger movement with an accuracy of about 86%. Fourteen years later, Tsenov, Zeghbib, Palis, Shoylev, and Mladenov (2006) proposed and developed a myoelectric recognition system using multilayer perceptron (MLP) for finger movement cases. MLP classified four finger movements using time-domain (TD) feature and achieved an accuracy of 93% using two EMG channels and 98% using four EMG channels. In addition to the researchers above, Tenore et al. (2009) employed MLP in their pattern recognition system. Different from previous approaches that worked on healthy subjects only, the system was also applied to the amputees. The system could recognize individual finger flexion and extension by the accuracy of on average 90%. The result also showed that the accuracy between the amputee and the able-bodied subjects is not significantly different.

Literatur review

The classical problems of the artificial neural networks (ANNs), which need a heuristic architectural process and take much training time, encourage the researchers to find alternative classifiers. Cipriani et al. (2011) utilized *k*-nearest neighbour (*k*-NN) as a classifier in their M-PR. The proposed M-PR extracted features using time domain features (TD) from nine EMG channels on five able-bodied subjects and five amputees. The experimental results showed that the system could classify seven finger movements with an accuracy of around 79% and 89% on the amputees and non-amputees, respectively. In addition, *k*-NN has a faster processing time and easier setup than ANNs.

In the recent decade, many researchers have been interested in support vector machine (SVM). Some published works show that SVM is more powerful than ANNs and used widely in many areas including myoelectric pattern recognition system (Khushaba, Kodagoda, Takruri, & Dissanayake, 2012; Oskoei & Hu, 2008),

it can perform a large number of finger configurations. Another example of a bionic hand that is available in the market is a

combined finger movements on the amputees and non-amputees. ELM consists of two groups: the node-based and the kernel-based ELM. The node-based ELM depends on the activation function of the node while the kernel-based ELM relies on the kernel function of the hidden layer. This paper covers these two ELM groups. This paper presents the comparison of ELMs and other well-known classifiers such as linear discriminant analysis (LDA), *k*-nearest neighbourhood (kNN), support vector machine (SVM) and least-square SVM (LS-SVM).

Research Aim

In addition to the classifiers, this paper investigates the combinations of various time-domains (TD) and autoregressive features to improve the performance of the M-PR. Not only that, this paper investigates the several feature projections to improve the class separability to enhance the classification performances.

Therefore, the contributions of this paper are firstly, it presents a deep and thorough investigation on the performance of ELMs in the myoelectric pattern recognition on the amputees and non-amputees. Secondly, it presents the observation on the features combination that can enhance the classification performance along with ELM. Finally, the paper investigates the optimal feature projections that can work with ELM to improve the performance of M-PR for the individual and combined finger movements on the amputees and non-amputees.

Highlights/main contribution

The paper is organized as follows. The next section presents the methodology consisting of the data acquisition procedure, data segmentation, feature extraction, dimensionality reduction techniques, classification, and post-processing. Section 3 provides the experimental results, and analysis for the segmentation, feature extraction, classifiers, and post-processing on classification accuracy. Afterwards, Section 4 presents the discussion, and finally, Section 5 provides the conclusions.

EXAMPLE #2

- **Reviewer #2:** The manuscript is largely an empirical evaluation of the so-called ELM to the problem of classification and recognition of myoelectric patterns. Whilst the subject might be of relevance, I have serious reservations about the content and quality of the current submission
- 1. **Novelty**. The proposed architecture **is not new**. In fact, it can be viewed as a trivial ensemble of WNN run on a pre-processed data. The pre-processing in this case is achieved by random projections which is now a classical tool for dimensionality reduction and improving statistical power of the model.
- 2. **Literature**. **Literature review is not complete**. Recent works, including those highlighting possible performance implications for ELMs, need to be discussed. See, e.g. Gorban et al. Approximation with random bases: Pro et contra. Information Sciences; Gorban et al. The blessing of dimensionality: Separation theorems in thermodynamic limit. In Proceedings of the 2nd IFAC Workshop on Thermodynamic Foundations of Mathematical Systems Theory, Spain, 28 - 30 September, 2016, Volume 49, issue 24, pages 64-69.DOI: http://dx.doi.org/10.1016/j.ifacol.2016.10.755

METHODOLOGY

- Apakah menjelaskan **secara rinci** tentang bahan dan metode yang digunakan, sehingga penelitian ini dapat diulang sepenuhnya bagi siapa saja yang ingin melakukannya.
- Apakah asal data atau sumber data repository diberikan secara lengkap (misalkan., catalog, numbers for museum specimens, digital data repositories)?
- Apakah ada ijin etika penelitian / ethical clearance (ijin pengumpulan data, survey ke manusia, percobaan pada manusia/hewan)
- apakah ukuran sampel cukup untuk melakukan pengujian dan mendukung kesimpulan?

METHODOLOGY

Apakah metode yang digunakan (termasuk statistik) sesuai untuk menguji hipotesis? Apakah ada pelanggaran asumsi untuk pengujian yang digunakan?

Bagian instrumen, apakah sudah dijelaskan dengan benar? Pembaca harus mengetahui tujuan, isi, jenis, reliabilitas dan validitas instrumen. Bagaimana instrumen diterapkan pada subjek / pengguna?

Apakah persamaan, gambar diberi label dengan jelas, mudah diikuti, dan benar?

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EXAMPLE #1

Anam, K., & Al-Jumaily, A. (2017). Evaluation of extreme learning machine for classification of individual and combined finger movements using electromyography on amputees and non-amputees. *Neural Networks*, *85*, 51–68. https://doi.org/10.1016/j.neunet.2016.09.004

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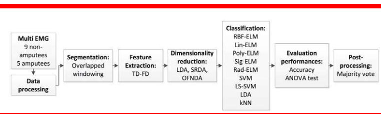

Fig. 2. The proposed pattern recognition for classifying finger movements on the amputee and non-amputee subjects using various kinds of ELM and other well-known classifiers.

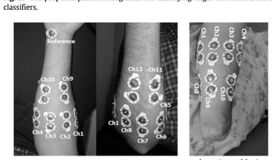

Fig. 3. Electrode's position example of an intact-limbed subject and an amputee subject.

3.2. Data acquisition and processing

3.2.1. Subjects

EMG signals employed in this work were collected by Al-Timemy et al. (2013). Nine able-bodied subjects, six males and three females aged 21–35 years and five traumatic below-elbow amputees aged 25–35 years participated in the data collection. Table 1 presents the demographics of the amputees. The electromyography signals came from twelve pairs of self-adhesive Ag–AgCl electrodes forming twelve EMG channels that were located on the right forearms of the intact-limbed subjects. Meantime, the amputees used eleven electrode pairs placed on the forearms by considering different levels of trans-radial amputation. Fig. 3 depicts the placement of the electrodes.

3.2.2. Acquisition device

A custom-built multichannel EMG acquisition device developed by Al-Timemy et al. (2013) was used to record the EMG signals. It consists of a 1000-gain factor amplifier for each channel and two analogue filters (a fourth-order Butterworth low-pass filter with cut-off frequency of 450 Hz and a second-order Butterworth high-

3.2.3. Acquisition protocol

The non-amputee subjects were instructed to perform fifteen (15) actual finger movements. As for the amputee subjects, they were asked to imagine moving their fingers representing twelve (12) finger movements. The fifteen finger movements consisted of eleven individual finger movements, three combined ones, and one rest state. Different from the able-bodied subjects, the amputee subjects were asked to perform eleven (11) individual finger movements, as on the able-bodied subjects, and one rest state (R). The individual finger movements comprise a thumb abduction (Ta), thumb flexion (Tf), index flexion (If), and middle flexion (Mf). Then ring flexion (Rf), and little flexion (Lf). Moreover, it involved thumb extension (Te), index extension (Ie), middle extension (Me), ring extension (Re), and little extension (Le). As for the combined movements, they consisted of little and ring flexion (LRf), index, middle and ring flexion (IMRf), and middle, ring and little flexion (IMRLf). The normal subjects performed these combined movements only.

During the data recording, the users were sitting on a chair in front of a personal computer. The subjects put their arms on a pillow and produced distinct finger movements subsequently. They had a rest of 5–10 s between two consecutive movements. The final movement took 8–12 s for normal-limbed subjects and 5–10 s for amputees. As a note, Amputees A1 and A2 performed movements of 3–4 s shorter than the rest of the amputees. Moreover, each movement was repeated six times. All trials in a movement were combined and labelled with a class related to the movement.

3.2.4. The channel number

The number of channels utilized in myoelectric pattern recognition influences the performance of the system. We would like to investigate its influence and observe the feasibility of using fewer channels for finger movement recognition. In this paper, we reduce the number of channels by arranging the electrode locations in such a way that the number of electrodes on extension and flexion muscles is the same or similar. The order of electrode location is shown in Fig. 3. The left side of Fig. 3 displays the

the straightforward exhaustive search algorithm (Li, Schultz, & Kuiken, 2010) which explores all possible electrode combinations, and the channel elimination (Al-Timemy et al., 2013) which eliminates the least contribution channel in each elimination iteration.

3.2.5. Data segmentation

In general, the data or signal can be segmented in two ways: either as a disjoint or overlapped windowing. The disjoint windowing only associates with the window length. On the other hand, the overlapped windowing is associated with the window length and window increment. The window increment is a period between two consecutive windows. In general, the disjoint windowing is overlapped windowing in a condition where the window increment is equal to the window length. Also, the window increment should not be more than the window length (Oskoei & Hu, 2008). Moreover, it should not be greater than the total time of the recognition system (Oskoei & Hu, 2007).

The determination of window length should consider the optimal delay time of a myoelectric control system (MCS), as defined by Farrell and Weir (2008) as:

$$D = \frac{1}{2}T_{wl} + \frac{n}{2}T_{inc} + \tau \qquad (28)$$

where D is the MCS delay time, and T_{wl} is the length of the window. Meanwhile T_{inc} is the increment of the window, n is the number of votes in the post-processing stage and τ is the processing time taken by a pattern-recognition system.

In addition to the segmentation method, the features are extracted from the signal on the steady state of the muscle contraction excluding the transient state. The classification process on the transient state necessitates muscle contraction from the rest state. In fact, in a real-time application, the switching happens from one movement to another, not from the rest state. Moreover, Englehart, Hudgins, and Parker (2001) found that the classification performance of the steady state outperforms that of the transient state. However, ignoring the transient state will reduce the robustness of the pattern recognition.

3.2.6. Feature extraction

Time domain (TD) and autoregressive (AR) features provide a robust feature set for an EMG signal recognition system (Hargrove et al., 2007; Tkach, Huang, & Kuiken, 2010). A single TD feature

value slope), RMS (root mean square), and sixth order of autoregressive model (AR6). We tested this new feature set on ten different window lengths. Then we compared its performance with other well-known feature sets, such as the feature set of Hudgins (MAV+MAVS+SSC+ZC+WL) (Hudgins, Parker, & Scott, 1993), Englehart (MAV+ZC+SSC+WL) (Englehart & Hudgins, 2003), Khushaba (SSC+ZC+WL+HTD+SKW+AR5+MAV) (Khushaba et al., 2012) and Hargrove (MAV+MAVS+SSC+ZC+Wl+RMS+AR5) (Hargrove et al., 2007). The theoretical explanation of these features is presented in Table 2.

3.2.7. Dimensionality reduction

All features extracted from all EMG channels are concatenated to form a large feature set. As a result, the dimension of the feature set is enormous and needs to be reduced without compromising the information contained in the original features. To reduce the feature dimension, we employed supervised feature projections, that is, linear discriminant analysis (LDA) (Fukunaga, 2013). Besides, we employed the extension of LDA, which is spectral regression discriminant analysis (SRDA) (Cai, He, & Han, 2008), and orthogonal fuzzy neighbour discriminant analysis (OFNDA) (Khushaba, Al-Ani, & Al-Jumaily, 2010). In LDA, the feature sets are reduced and projected to $c - 1$ features where c is the number of classes.

3.2.8. Classification

This work investigates the performance of extreme learning machine (ELM) (see Section 2 for the ELM's theory) in finger movement classification. In general, the ELM can be divided into two groups, node-based ELM and kernel-based ELM. They are different in the feature mapping. The node-based ELM utilizes hidden layer nodes to map the features while the kernel-based ELM employs the kernel function. In this work, we used a sigmoid-additive hidden node (Sig-ELM) and a multi-quadratic radial-basis-function hidden node (Rad-ELM) for the node-based ELM. As for the kernel-based ELM, we employed linear (Lin-EM), polynomial (Poly-ELM), and RBF kernels (RBF-ELM).

Some experiments were performed to compare classification performances among different types of ELMs with respect to the classification accuracy. Besides, comparison with other well-known classifiers, such as the SVM, LS-SVM, kNN and LDA, was also carried out. Also, except for kNN and LDA, the SVM, and the kernel-based ELM require parameter optimization. The RBF kernel, Reviewer #2: This paper cites examples of human body loss, historical results of prosthetic research, and discusses the psychological and functional loss caused by physical disability. From this perspective, for the assisted EMG control system for prosthetics (especially the hand), a comparison is made between the classification control scheme and the regression control scheme. A new type of simultaneous proportional MCS random forest is proposed and evaluated. For single-layer neural networks.

The study of EMG assisted control is very important and plays an important role in the development of prostheses for the disabled. The random forest proposed in the article provides a way to implement the regressor on a single board computer. The results of the third stage show that the performance of random forests that predict all sensor targets simultaneously is better than single prediction, and random forests can become another solution for multi-target prediction. Compared with deep neural networks, the prediction time and hyperparameters are greatly reduced.

EXAMPLE #2

Disadvantages:

1. The random forest algorithm step part, although the original text is cited, the similarity is too high.
2. During the random forest test for different numbers of trees, while performing grid search optimization, some optimization of parameters should also be taken.
3. When comparing with other regression variables, it should also be tested under the same conditions as the regression variables that support multiple output prediction to verify the objectivity of the results.
4. Unfortunately, there is no physical experiment to verify the performance of the random forest proposed in the article on actual devices.

EXAMPLE #3

Major Issues:

•This paper relates to the field of robotic rehabilitation, and the content may be more appropriate and of interest to Transactions on Biomedical Engineering or Transactions on Neural Systems and Rehabilitation Engineering.

•Methodological descriptions are scattered throughout four different sections of this paper. It is therefore not entirely clear what the exact experimental protocol was for both the offline and online experiments, making it difficult to judge the quality of the experimental design. Please rearrange the information presentation of the paper to make this more apparent.

•Section II (P. 2): The RBF extreme learning machine appears to be a slight modification of the randomized RBF neural network of Broomhead and Lowe (Complex Systems, 1988). The authors should cite this paper or others appropriately and consider adjusting terminology accordingly.

•Section III (P. 3): The pattern recognition system uses only two EMG electrodes, despite the current literature indicating that at least four are necessary for good pattern recognition performance, with six to eight being preferred (Parker et al., J Electromyogr Kinesiol, 2006; Hargrove et al., IEEE Trans Biomed Eng, 2007).

•Section IVC (P. 7): The statement that the exoskeleton is "not good for the user's safety" due to its lack of physical sensors is immensely troubling, and casts concerns on ethics of the study. There is no information regarding ethics board approval and adherence to the Declaration of Helsinki. This is a serious issue that, without remedy, will preclude the publication of these results.

RESULTS

Bagian hasil harus menyajikan HANYA hasil dari penelitian. TIDAK ADA referensi untuk studi sebelumnya. Harus eksplisit dan jelas apa yang kita hasilkan

Apakah bagian hasil melaporkan data dari semua metode yang digunakan?

Apakah semua hasil didokumentasikan dengan tepat oleh teks, gambar, grafik, dan tabel? apakah kualitas gambarnya sesuai?

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EXAMPLE #1

3.1.2. Shape-parameter ξ

This section varied the value of shape parameter ξ in Equation (11). The shape parameter is varied among 0.1, 0.2, 0.3, 0.5, 2 and 5. The value of the parameter p_m is 0.5 following the result in section 0. Furthermore, g is equal to 10000. The experimental result is presented in Figure 5.

Figure 5 indicates that $\xi = 2$ converged earlier than the others did. The final fitness value of it is the second worst after $\xi = 5$. On the other hand, the small value of ξ gave a good optimization process. These facts imply that the high value of ξ is not a good option for optimization of SW-RBF-ELM. The best optimization process is shown when $\xi = 0.2$.

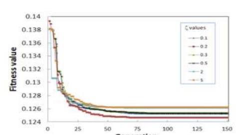

Figure 5. The fitness values for variable ξ when $p_m = 0.5$ and g = 10000 over eight subjects

Table 2 draws different finding from Figure 5. The table shows that SW-RBF-ELM with $\zeta = 0.1$ achieved the highest average accuracy, not $\zeta = 0.2$. Besides, it attains the highest accuracy across four subjects, which is similar to $\zeta = 0.2$. By considering the fitness value and the average accuracy performed, $\zeta = 0.2$ is selected as the optimal shape parameter.

Table 2. The accuracy of SW-RBF-ELM when p_m=0.5 and g=10000 using 3-fold cross validation

Subject	ζ (Accuracy in %)					
	0.1	0.2	0.3	0.5	2	5
S1	92.869	92.869	92.869	92.869	92.869	92.869
S2	98.028	98.129	98.028	98.098	98.028	98.028
S3	95.893	95.440	95.893	95.139	95.070	95.139
S4	93.310	93.344	93.310	93.344	93.240	93.309
S5	96.731	96.731	96.660	96.731	96.660	96.731
S6	97.321	97.250	97.250	97.250	97.215	97.123
S7	94.106	94.038	94.002	94.004	93.898	93.898
S8	97.845	97.880	97.880	97.845	97.845	97.845
Average	95.763	95.710	95.737	95.660	95.603	95.618

*The underlined value is the highest one

3.1.3. Parameter g

The previous two experiments have selected two optimum parameters, $p_m = 0.5$ and $\zeta = 0.2$. This section tries to get the optimum g parameter. The parameter g (Equation (11)) is varied from 100, 1000, 10000 and 100000. The experimental results are presented in Figure 6.

Figure 6 depicts the fitness values of four different g values. This figure indicates that the big number of g value give better accuracy than the small one. The g = 10000 exhibits the best performance. This fact is supported by the accuracy of SW-RBF-ELM in Table 3.

TL is mostly misclassified to the movement L by accuracy 2.65 %. Nevertheless, it did not occur in all combined movements. In addition to Table 4, Figure 9 helps the reader the get a visual graph of the confusion matrix.

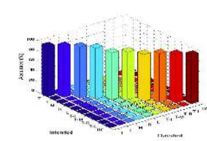

Figure 9. The confusion matrix plot of the classification result of SW-RBF-ELM

3.1.6. SW-RBF-ELM and other well-known Classifiers

In this experiment, the performance of SW-RBF-ELM is compared to other well-known classifiers such as original ELM using sigmoid activation function (Sig-ELM), SRBF-ELM, SVM, LDA, and kNN. The experimental results are depicted in Figure 10.

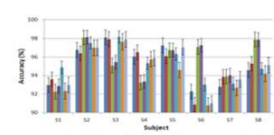

Figure 10. The accuracy of SW-RBF-ELM and other well-known classifiers for finger movement recognition using 3-fold cross validation

Figure 10 shows that SW-RBF-ELM is the most accurate classifier among seven different classifiers in recognizing ten finger movements using EMG channels across eight able-bodied subjects. This finding is supported by Table 5 that presents the average accuracy achieved by each classifier. SW-RBF-ELM achieved the accuracy of 95.71 %. Furthermore, SW-RBF-ELM achieved the highest accuracy on four subjects, while it attained the second lowest accuracy on the subject S3 and S4.

Table 5. The accuracy of various classifiers for the finger movement recognition using 3-fold cross validation

Classifier	Accuracy	
	Mean (%)	STD
Sig-ELM	95.10	2.25
RBF-ELM	95.06	2.21
SRBF-ELM	95.54	2.23
SW-RBF-ELM	95.71	2.09
SVM	95.39	1.86
LDA	94.37	2.38
kNN	95.06	2.37

Anam, K., & Al-Jumaily, A. (2018). Optimized kernel extreme learning machine for myoelectric pattern recognition. *International Journal of Electrical and Computer Engineering*, *8*(1). https://doi.org/10.11591/ijece.v8i1.pp483-496

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EXAMPLE #2

Major points

1.The described algorithm is a valid and interesting approach to increase performance of MCSs. However, by mixing up methods, results and discussion in section III and IV structure of the paper is not very clear and, therefore, hard to understand for the reader (e.g. page 4 lines 33 - 50 right column, page 5 lines 1 – 15 left column). As a consequence, crucial points can't be easily filtered out and makes following the manuscript difficult.

•Section IVA (P. 6): What statistical tests were used to derive the conclusion that RBF-ELM-R outperformed other classifiers in the offline experiment? The statement in Section V that a one-way ANOVA was used is not sufficient to explain or defend the process used. What post hoc tests and corrective methodologies were used? Given the magnitude of the difference versus the error bars in Fig. 7, it is difficult to determine whether these differences are truly significant, and if so, under what circumstances. Again, a comparison of active and total errors would better describe the performance of the proposed classifier against established ones.

DISCUSSION & CONCLUSION

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Diskusi harus menghubungkan hasil studi dengan data yang telah dipublikasikan sebelumnya. Mengulangi hasil tidak perlu dan tidak diinginkan

Apakah hasilnya dibahas dengan tepat?

apakah batasan dan penelitian masa depan dibahas?

Apakah hasil dapat mendukung kesimpulan?

EXAMPLE #1

Table 4 Mean and standard deviation of classification accuracies for movement reduction obtained from the SRELM feature extraction and the NN classifier using the EMG signals from CH3 and CH6

No. of movements	Mean ± SD	Movement removal
14	85.38 ± 4.55	–
13	99.08 ± 0.68	M7
12	99.28 ± 0.59	M7 and M13
11	99.94 ± 0.19	M7, M13, and M6
10	100.00 ± 0.00	M7, M13, M6, and M14

channels, and one channel, respectively. The results show that the classification accuracy decreases from 99.57 to 58.95% when the number of channels decreases from 6 to 1. Moreover, to obtain a high classification accuracy, EMG signals from the muscles located on the anterior and posterior compartments of the forearm are needed. For example, the maximum classification accuracy from two EMG channels at 85.38% can be obtained from the combination of flexor carpi radialis (CH3) and extensor carpi ulnaris (CH6), which are located on the anterior and posterior compartments of the forearm, respectively.

Table 4 presents classification accuracies from movement reduction using two channels of EMG signals, namely CH3 and CH6. The selection of these two EMG channels was guided by Table 3. The subset of finger movements was optimized by considering classification accuracy of each movement. All EMG signals from 14 finger movements were firstly classified, and then the classification accuracy was individually investigated for each movement from the confusion matrix [31]. The movement providing the lowest classification accuracy was removed from the movement set. The procedure was repeated until the number of movements decreased to two movements. The results show that the classification accuracy increases from 85.38 to 100% when the number of movements decreases from 14 to 10 movements. In other words, the reduction in the number of movements decreases the complexity of classification, resulting in better classification accuracy.

5 Discussion

Results of the scatter plot shown in Fig. 4 and the RES index shown in Fig. 5 show that the reduced feature vectors from SRELM provide the best performance in separating finger movements. Anam and Al-Jumaily [18] reported that SRELM is an ELM for supervised feature extraction with consideration of the class label. The aim of the training is to produce output that is very close to the output target. In other words, the training tries to minimize the error between the actual output and target. As a result, the reduced feature vectors from SRELM show better performance in separating 14 finger movements than those from other feature extractions. In addition, LDA considers also class label in the extraction step (i.e., supervised feature extraction) and ULDA is developed to solve the limitation of LDA by producing a set of uncorrelated discriminant features employing the singular value decomposition [14]. In contrast, as Chu et al. [32] reported the PCA does not consider the class labels in the extraction process (i.e., it performs unsupervised feature extraction). Therefore, the output is another representation of the reduced feature vectors and its performance is lower than with other feature extraction techniques.

Table 5 Performance comparisons with other techniques from previous publications

Ref.	#M	#Ch	Features in each EMG channel	#DF	FE	Classifiers	Acc. (%)
[8]	8	2	MAV, SGT	16	–	NN	85.10
[9]	5	2	FFT	20	–	NN	86.00
[13]	10	2	7th-order AR coefficient, SSC, ZC, WL, SKW, HTD	28	LDA	SVM	≈ 92.00
[18]	10	2 + 1	6th-order AR coefficient, SSC, ZC, WL, SKW, MAV, HTD	42	SRELM	AW-ELM	86.73
[A]	10	2	4th-order AR coefficient, SSC, ZC, WL, SKW, MAV, MNF, KURT	22	SRELM	NN	100.00
[11]	12	32	WL	32	PCA	NN	94.30
[12]	15	6	6th-order AR coefficient, RMS, WL, ZC, IEMG, SSC	66	OFNDA	LDA	98.25
[19]	11	7	IEMG, WL, VAR, ZC, SSC, WAMP	42	–	NN	93.90
[20]	15	4	4th-order AR coefficient, WL, RMS	24	–	SVM	97.60
[B]	14	6	4th-order AR coefficient, MAV, WL, ZC, SSC, MNF, KURT, SKW	66	SRELM	NN	99.57

#M the number of movements, *#Ch* the number of EMG channels used, *#DF* the dimension of the feature vector before applying feature extraction, *FE* feature extraction, *Acc* accuracy, *SGT* the spectra from Gabor transform, *FFT* fast Fourier transform, *HTD* Hjorth time domain, *IEMG* integrated EMG, *VAR* variance of EMG, *RMS* root mean square, *[A]* the proposed method when using two-EMG channels for classifying 10 finger movements, *[B]* the proposed method when using six-EMG channels for classifying 14 finger movements

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Table 5 presents the performance comparisons of the proposed method with those from previous publications. The classification performance can be divided into two groups. In the first group, the number of EMG channels used is 2 [8, 9, 13, 18, A]. The dimensions of feature vectors from [8, 9] are 16 and 20, respectively. The classifier used is NN. The classification accuracy is 85–86%. It is important to note that there is no application of feature extraction for classifying movements from both individual and combined fingers in [8, 9]. This may be the cause of poor classification accuracy. However, feature extraction is applied for reducing a dimension of the feature vector in [13, 18, A]. The classification accuracy of the proposed technique for classifying 10 movements from two-channel EMG signals achieves 100% [A] compared to 86.72 and 92.00% in [13, 18], respectively. Note that, in [18], the feature vectors were generated from two EMG channels plus one channel formed from summation of the two channels. Moreover, Bayesian fusion was applied as a post processing in [13]. The comparison between [A] and [18] indicates that the pairing of a feature extraction technique with a type of classifier affects the classification accuracy. Another way to increase classification accuracy when the number of movement increases is to increase the number of EMG channels as shown in [11, 12, 19, 20, B]. Results show that the proposed technique achieves good accuracy in classifying 14 movements from six-channel EMG signals at 99.57% [B]. The results of this study clearly illustrate that using high-dimensional feature vectors with feature extraction could improve the classification performance.

6 Conclusions

This paper proposed a system for classifying 14 finger movements, involving individual and combined finger flexion observed by six channels of EMG signals. Six feature extraction techniques were evaluated including principal component analysis (PCA), linear discriminant analysis (LDA), uncorrelated linear discriminant analysis (ULDA), orthogonal fuzzy neighborhood discriminant analysis (OFNDA), spectral regression linear discriminant analysis (SRLDA), and spectral regression extreme learning machine (SRELM). The results show that the reduced feature vectors from SRELM give the best performance in terms of feature separation among these feature extraction techniques. In addition, the best feature separation ability obtained with SRELM was confirmed by a quantitative measure, namely the RES index. Subsequently, seven classifiers were validated, namely support vector machine (SVM), linear classifier (LC), naive Bayes (NB), k-nearest neighbors (KNN), radial basis function extreme learning machine (RBF-ELM), adaptive wavelet extreme learning machine (AW-ELM), and neural network (NN). The results show that NN provides the best performance in separating

REFERENSI

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Referensi harus relevan dan beberapa di antaranya harus baru (5 atau 10 tahun terakhir)

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Originalty and Novelty
- Konten Ilmiah: Akurasi dan Kebaruan

Quality
- Kualitas Metodologi
- Kualitas pekerjaan

Presentation and Organization
- Gambar, teks, tabel, dll

Readability
- Kejelasan

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- **Contoh jawaban dari editor terhadap jurnal yang ditolak:**
  "It is with regret that we must inform you that your manuscript has been declined for publication in … "

- **Sementara yang harus revisi:**
  "It has been reviewed by experts in the field and we request that you make minor revisions before it is processed further. Please find your manuscript and the academic editor's comments at the following link:"

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TIP-1:

Jangan berkecil hati jika tidak diterima (*declined*). Tetap bersyukur karena tulisan yang kita buat telah sempat dibaca oleh *reviewer* yang telah bersedia meluangkan waktu untuk membacanya. Untuk yang harus direvisi jangan terlalu gembira karena harus merespon pertanyaan-pertanyaan *reviewer* yang sangat menentukan lolos atau tidaknya tulisan yang kita kirim.

Pegalaman tiap penulis mungkin berbeda-beda terhadap tulisan yang harus direvisi. Saya sendiri sangat kaget dengan komentar *reviewer* yang kebanyakan di luar dugaan. Mereka kebanyakan sudah berpengalaman me-*reviewer* jurnal sehingga mampu mendeteksi kesalahan-kesalahan yang ada dalam naskah yang mereka cek

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Berikut ini contoh bagaimana membalas/merespon pertanyaan reviewer. Kata pembuka jangan lupa ditulis:

"We thank the editor and reviewers for their thorough reading of our manuscript and their comments and suggestions that helped us to improve the manuscript. As indicated below, we have tried to do our best to respond to all the points raised. Please contact me if you need any further information".

Sangat sederhana, tetapi cukup sopan dan mudah-mudahan bisa mengurangi 'kegarangan' para *reviewer*.

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MERESPON PERTANYAAN REVIEW/EDITOR JURNAL

TIP-3:

Selanjutnya adalah menjawab dengan memberitahu bagian yang direvisi. Untuk naskah yang menggunakan penomoran, nomor yang menunjukan baris tulisan sedikit memudahkan proses revisi.

***C1.** Your dataset is based on 30m spatial resolution basemaps provided by Bing, Google, other sources (require detail explanation). I fully understand why you used this manual method. But you should validate accuracy of your dataset with using an alternative available data. As I understood from your paper, remote sensing data is not available or not in good quality. However, you may find another dataset which covers a part of your site, then you can validate accuracy of your dataset. This is important, because errors in your dataset may mislead you about results.*

A1.

Thank you for the suggestion. The remote sensing data from USGS (August 2015) were used to validate, especially for built-up class. Figure below (blue region) shows the built-up class shown in Google earth Pro after classification using IDRISI selva 17. We have added the following text. Line 130:"
However, remote sensing data from USGS (August 2015) was used to validate current LU data in regard to built-up class".

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Terima kasih