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# Hand/arm gesture segmentation by motion using IMU and EMG sensing

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**Abstract**

Gesture recognition is more reliable with a proper motion segmentation process. In this context we can distinguish if gesture patterns are static or dynamic. This study proposes a gesture segmentation method to distinguish dynamic from static gestures, using (Inertial Measurement Units) IMU and Electromyography (EMG) sensors. The performance of the sensors, individually as well as their combination, was evaluated by different users. It was concluded that when considering gestures which only contain arm movement, the lowest error obtained was by the IMU. However, as expected, when considering gestures which have only hand motion, the combination of the 2 sensors achieved the best performance. Results of the sensor fusion modality varied greatly depending on user. The application of different filtering method to the EMG data as a solution to the limb position resulted in a significative reduction of the error.



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## 1. Introduction

One of the most intuitive methods for Human Machine Interaction (HMI) is gesture spotting: robots performing defined movements based on gestures which are performed by humans. These movements are generally executed in sequence in order to perform complex tasks. Multiple solutions have been presented for gesture spotting, such as gesture detection through body-worn sensors or using computer vision or even hybrid solutions.

Methodologies for gesture segmentation have been studied such as [1], that has tackled this problem using a data glove to detect hand and arm gestures performed by the user. In [2], the authors propose to use IMU sensors on a lower limb exoskeleton. According to [3], IMUs have some associated benefits in comparison to other sensors. The main advantages mentioned are: there is no inherent latency associated with this sensing technology; and all delays are due to data transmission and processing. Other major issue about IMU is drift [4].

Electromyography (EMG) is a method for recording and analyzing electric signals resulting from neuromuscular activity, also known as electromyograms. Using multi-channel EMG recordings it is possible to identify the movement being performed [5]. Classification performance of EMG features for hand and arm movements was studied using data from 15 EMG sensors placed on the forearm [6]. Contractions performed at different force levels may be very different from one gesture sample to another and therefore present a challenge to a pattern classifier [7]. The variation of limb position degrades myoelectric pattern recognition performance [8]. In [9] it was studied the effect of arm movements in EMG pattern recognition, including both static and dynamic arm motions. It was concluded that dynamic change of arm position had seriously adverse impact on sEMG pattern recognition. In [10] the authors claim that the hand gesture data is not as useful as it may appear. First, given that the hand gesture is calculated from the EMG data measured on the skin of the forearm, which is a side effect of the muscle movement, there is a possibility that the calculated gesture may not loyally indicate the actual gesture of the hand. Second, when exterior forces are applied to the muscles or there is some other interference with the EMG readings such as tight clothes, the accuracy of the measurement can be vastly degraded, to the point where the gesture data may not be usable at all. According to [11], multimodal sensor fusion combines information from different sensor modalities to overcome the shortcomings of each sensor. An example of this application can be seen in [12], where a system for recognizing hand and finger gestures is presented, and the achieved conclusion is that the system benefits from the combination of both sensor modalities. An example of this application can also be seen in [13], where an accelerometer is used in conjunction with EMG in order to improve classification results of arm movements.

This manuscript aims to evaluate the performance of IMU and EMG sensors in regards to gesture segmentation, aiming to distinguish dynamic motions from static postures.

## 2. Sliding window

In order to study both arm movements detected by IMU and hand movements detected by EMG, a sequence containing both was required. The motion sequence shown in Fig. 1 and performed in [1] was chosen, given its variety of movements, as well as to allow a comparison between both studies. The sequence is composed of 8 different dynamic movements, including both arm and hand movements, which are signaled in green. While some are clearly identified by numbers (#2, #4, #5, #7 and #8) the other 3 are movement epenthesis. They will throughout this manuscript be identified with a number according to their position in the sequence (#0.5, #2.5 and #5.5).

An important note to take from this sequence is that not all gestures are guaranteed to be detected by both the sensors of the armband, as some correspond to only arm gestures and some to only hand gestures, with the other sensor being an auxiliary source of information in those cases. The group of relevant gestures to be captured by the IMU sensor is $R_{IMU}$ = [#0.5, #2, #4, #5, #7, #8] and the group of relevant gestures which are to be captured by the EMG sensor is $R_{EMG}$ = [#2.5, #4, #5, #5.5, #7]. Gestures which only rely on arm gesture are $O_{IMU}$ = [#0.5, #2, #8] and those which only rely on hand movement are $O_{EMG}$ = [#2.5, #5.5].

A gesture segmentation process using a sliding window method was used to segment continuous data obtained from the IMU and EMG sensors. The sliding window method considers that there is motion if there are motion features above defined thresholds, thresholds calculated for each motion feature using a genetic algorithm as proposed in [1]. A sliding window is composed of *w* consecutive frames, being *w* the window size, and in each instant the window slides forward one frame, it is updated and evaluated. A static frame is only acknowledged as such if none of the motion features exceed the threshold within the sliding window.

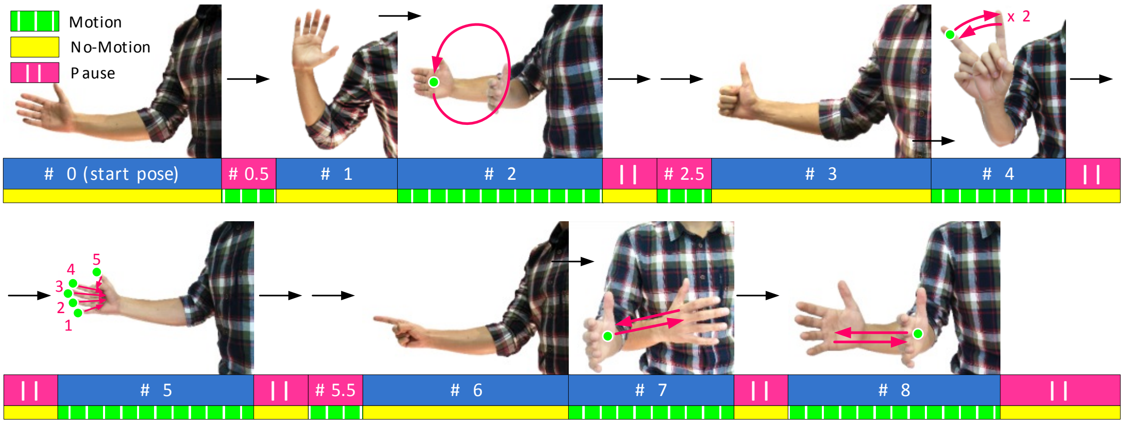


Fig. 1. Performed gesture sequence.

### *2.1. Sliding Window for IMU*

The features of the IMU were directly obtained from the IMU data, namely linear acceleration, angular velocity and orientation. The features are the difference between consecutive values of orientation.

Concerning the computation of the thresholds for the sliding window, a static data sequence was obtained (the user was stood up with the arm at rest and standing horizontally). The obtained values for the thresholds of linear acceleration, angular velocity and variation of orientation are $T_{IMU}=[0.04 \quad 9.03 \quad 0.04]$.

To find the ideal window size, different sensitivity factors for motion were used. Initially, using a sensitivity factor of 3, the minimum window size necessary to avoid false negatives was calculated to be of 9 frames, with a false negative occurring when the window size was lower. When increasing the window size above 9, the only noticeable difference was an increase in the sizes of the windows up to 39 frames, when the window became too large and different gestures were no longer discernible. In light of these results, the window size of 10 was defined as the minimum ideal value for the IMU sensor. Algorithm is below.

```
Algorithm SlidingWindowIMU(n,T,k,w,O)
Inputs:        n timestamp
               T threshold vector
               k threshold sensitivity factor
               w window size
               O observation matrix
Output:        M sliding window motion function

for i ∈ [1, LENGTH(T)] do ► Apply sensitivity factor
 t(i) ← k · t(i)
end for
T(1) ← T(1) + 1 ► Add gravity to acceleration threshold T(1)
F ← GetFeatures(O) ► Calculate features using equation of eclidian distance
for i ∈ [1, LENGTH(n)] do ► Obtain the motion binary function
  m(i) ← 0
  for j ∈ [1, LENGTH(T)] do
   m(i) ← (F(i,j) ≥ T(i)) V (F(i,1) ≤ (2 - T(1)) V m(i)
  end for
```

```
end for
for i ∈ [w, LENGTH(n)] do ► Apply sliding window function for motion detection
 for j ∈ [1, w-1] do
  M(i) ← m(i) V m(i + j)
 end for
end for
```

### 2.2. EMG Data Filtering

The treatment of EMG data, rectification of the data from the 8 EMG sensors was performed using the *abs* function. This was followed by a low-pass Butterworth filter in order to obtain the filtering coefficients, which are then applied to a zero phase digital filter. The parameters used were a sampling frequency of 200 Hz, in accordance to the EMG data frequency, a cut-off frequency of 3 Hz, and a filter order of 4, Fig. 2.

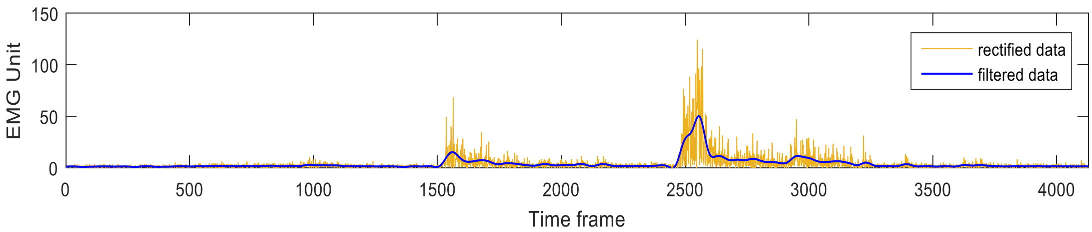


Fig. 2. Comparison of rectified data and filtered data from EMG sensor.

Multiple parameters were tested to detect and discern dynamic from static hand motion. The main objectives in looking for a good parameter were:

- Classify EMG patterns given the fact that EMG sensors do not have fixed positions, which can shift with every new usage of the armband;
- A method which allowed for a clear distinction between static and dynamic. Even when static, a certain muscle strength is required to maintain the gesture. As such, some EMG data values may be consistently high depending on the gesture being performed.

The features extracted from the EMGs signals are: Base values of EMG; Sum of values; Weighted sum of values; Variance of the sum of EMG signal; and Variance of the individual EMG signals.

For the study of the window size, two sensitivity factors were used based on the previous calculations, with values 6 and 8. According to the results, the minimum window size when using a factor of 6 is 50, and when using a factor of 8 is 60 to avoid errors in #2.5. Errors in #7 can be ignored as limits since it is mostly an arm movement, with the initial transition of the arm detected. These errors are likely to be solved when merging the sensors together. In the light of these results, the chosen sensitivity factor for the EMG sensor was 7.

## 3. Experiments, results and discussion

An analysis was made by observing the motion output obtained by the EXP method, which is the combination of EMG and IMU signals, and the EMG and IMU methods alone. The purpose of this process is to better detect which motion segments correspond to each gesture, as the sequences were executed at different paces and with the presence of errors. In addition, it is often difficult to discern between gestures.

For the validation of the proposed segmentation method, the sequence was performed 10 times by 2 different participants, participant A and B. The participants were requested to perform the sequence in Fig. 1. For EXP – Participant A, gestures #4 and #7, in the beginning of the gesture there is a transition motion of the hand as it changes its pose from the previous gesture, which is included within the gesture. In certain cases, this motion was performed before the arm movement, distant enough for there to be a discernible separation in the gesture. This error is therefore classified as a false negative, Fig. 3. In gesture #7 the segment detected by the EMG ends before the start of the IMU detected segment, resulting in a false negative. In Fig. 4 (participant B), a motion segment was detected by the EMG sensor in between gestures #2.5 and #4, which is identified as a false positive. Certain gesture segments have no breaks between one another, with motion being continuously detected. Under-segmentation (segment fusion) can be seen as a false positive which occurs in between two segments. When combining both sensors, the piling of data from both has also in some situations led to gestures being indiscernible.

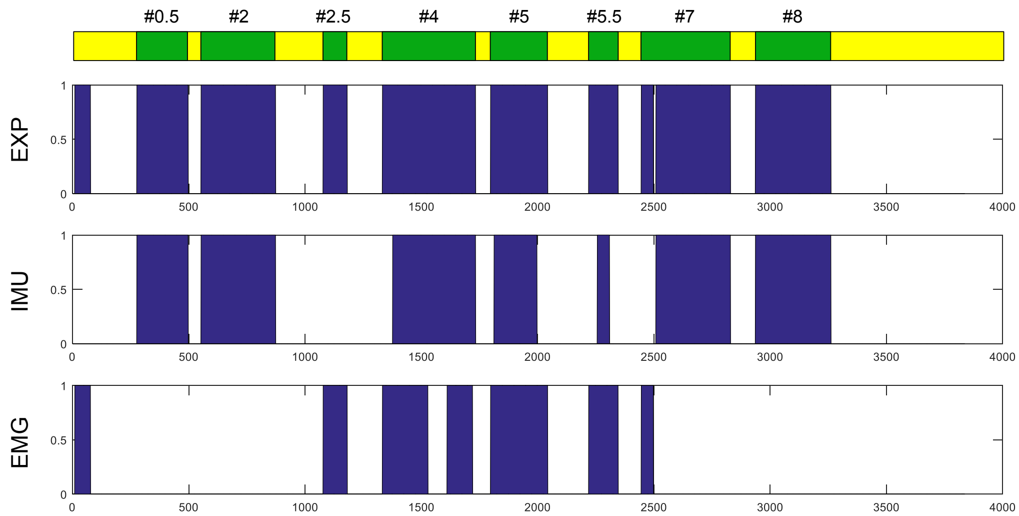


Fig. 3. Sample from participant A of the segmentation with the 3 methods: EXP (EMG + IMU), IMU and EMG.

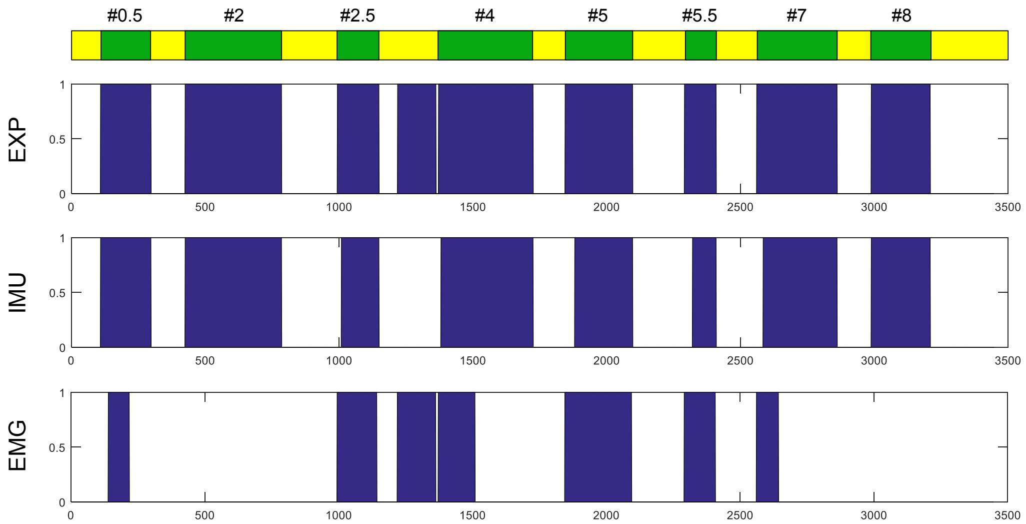


Fig. 4. Sample from participant B of the segmentation with the 3 methods: EXP (EMG + IMU), IMU and EMG.

The resulting segmentation error for both participants, A and B, and for the combination of both sensors, EXP, single IMU and single EMG are in Table 1, Table 2 and Table 3. It can be concluded that for EXP we have in general better results. Analyzing the errors, it can be seen that the EMG method is underperforming for every user. The musculature for all individuals was not similar, and therefore the ability for a consistently reliable contact between the armband's sensors and the skin could have decreased for individuals with thinner arms, harming the

EMG signal. While the position of the armband along the arm and the position of the IMU sensor relative to the arm were mostly similar, certain differences between users may have occurred, resulting in electrode shift in between participants.

Table 1. Segmentation error (%) based on gesture and participant for the EXP method.

| Participant/Method | #0.5 | #2 | #2.5 | #4 | #5 | #5.5 | #7 | #8 | FP | Total |
|---|---|---|---|---|---|---|---|---|---|---|
| A | 0 | 0 | 40 | 0 | 0 | 0 | 20 | 10 | 0.00 | 8.75 |
| B | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1.43 | 1.25 |

Table 2. Segmentation error (%) based on gesture and participant for the IMU method.

| Participant/Method | #0.5 | #2 | #2.5 | #4 | #5 | #5.5 | #7 | #8 | FP | Total |
|---|---|---|---|---|---|---|---|---|---|---|
| A | 0 | 0 | 50 | 0 | 30 | 70 | 0 | 10 | 0.00 | 20.00 |
| B | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.00 | 0.00 |

Table 3. Segmentation error (%) based on gesture and participant for the EMG method.

| Participant/Method | #0.5 | #2 | #2.5 | #4 | #5 | #5.5 | #7 | #8 | FP | Total |
|---|---|---|---|---|---|---|---|---|---|---|
| A | 80 | 60 | 70 | 80 | 0 | 0 | 40 | 70 | 0.00 | 50.00 |
| B | 60 | 70 | 10 | 50 | 0 | 20 | 10 | 100 | 1.43 | 41.25 |

Given the weak performance of the EMG signal, new pre-processing options were studied. One of the solutions found was the application of a bandpass filter prior to the application of the already existing filter, in an attempt to remove motion artefact which causes errors related to limb position. The application of the filter can be seen in Fig. 5, in which 2 stages of filtering can be observed: the resulting data from the application of the bandpass filter and rectification, and the data after the filtering process.

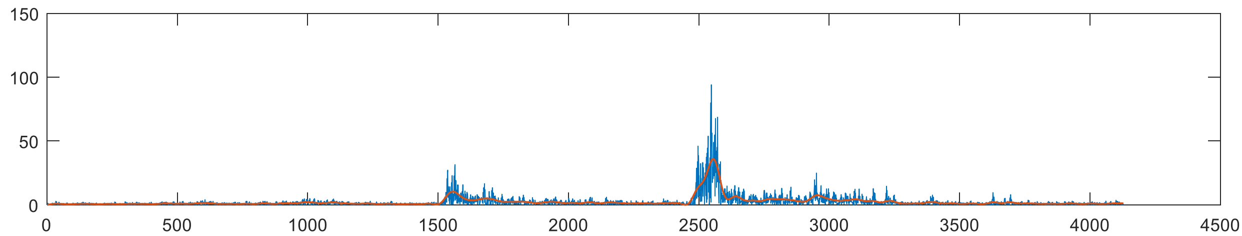


Fig. 5. Bandpass filter, rectification, and with lowpass filter, from EMG sensor.

In the analysis of this filter, using the initial sequence, it was noted that the new method using both sensors could not detect gesture #5.5, but presented smaller segments than in the former method, as seen in Fig. 6. When altering the sensitivity factor, the detection of the gesture could not be made without damaging the remaining gestures.

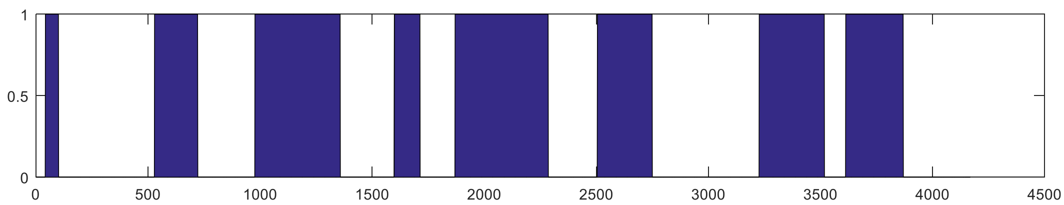


Fig. 6. Resulting sequence segmentation from the application of the modified EXP method.

The filter was then applied to the sequences for both participants. The EXP method improved with the new filter, with a new total segmentation error of 3%, compared to the unchanged segmentation error of the IMU sensor of 10%. The noticeable change is that all gestures, with the exception of gesture #8, obtained the same of better results with the EXP method compared to the IMU method. This is due to a decline in the number of undersegmentation errors in the sequences due to the removal of low-frequency noise from EMG sensor. The EMG filter is still capable to detect a majority of the hand gestures, which can be seen since the EXP method presents better results than the IMU method when considering hand gestures.

Overall, the performance of the sensor fusion method has improved with the application of a different pre-processing method. The study into other filtering options could further improve the segmentation, as well as the estimation of new parameters for segmentation.

## 4. Conclusion

This paper presented a study to analyse gesture segmentation by motion using different sensors, IMU, EMG and the combination of both. Results indicate that segmentation error for EXP (IMU + EMG) is close to the error achieved with the IMU alone. However, the EMG signal is important to detect when the fingers are moving. In the other hand, the EMG signal corrupts some arm motion gestures. With a second approach aimed at solving the error from limb position using a different filter, the combination of sensors achieved a lower segmentation error. Additional efforts to this work could be dedicated to further improving EMG motion segmentation by exploring other pre-processing methods. Similarly, an adaptive threshold for gesture segmentation was not used in this work.

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## References

[1] M.A. Simão, P. Neto, O. Gibaru, IEEE Trans. Ind. Informatics, IEEE (2016) 1–11.
[2] J.Y. Jung, W. Heo, H. Yang, H. Park, Sensors (Switzerland) 15 (2015) 27738–27759.
[3] H. Fourati, N. Manamanni, L. Afilal, Y. Handrich, IEEE/ASME Trans. Mechatronics 19 (2014) 149–157.
[4] P. Neto, J.N. Pires, A.P. Moreira, in:, IECON 2013 - 39th Annu. Conf. IEEE Ind. Electron. Soc., IEEE, 2013, pp. 4026–4031.
[5] A. Alkan, M. Günay, Expert Syst. Appl. 39 (2012) 44–47.
[6] H.M. Al-Angari, G. Kanitz, S. Tarantino, C. Cipriani, Biomed. Signal Process. Control 27 (2016) 24–31.
[7] E. Scheme, K. Englehart, J. Rehabil. Res. Dev. 48 (2011) 643–660.
[8] A. Radmand, E. Scheme, K. Englehart, in:, 2014 36th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBC 2014, IEEE, 2014, pp. 662–667.
[9] J. Liu, D. Zhang, X. Sheng, X. Zhu, Biomed. Signal Process. Control 13 (2014) 189–197.
[10] S. Weili, (2014).
[11] D. Novak, R. Riener, Rob. Auton. Syst. 73 (2015) 155–170.
[12] M. Georgi, C. Amma, T. Schultz, Proc. Int. Conf. Bio-Inspired Syst. Signal Process. (2015) 99–108.
[13] A. Fougner, E. Scheme, S. Member, A.D.C. Chan, S. Member, K. Englehart, S. Member, Ø. Stavdahl, (2011) 4247–4250.