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Optimizing activity recognition in stroke survivors for wearable exoskeletons

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***Abstract*— Stroke affects the mobility, hence the quality of life of people victim of this cerebrovascular disease. Part of research has been focusing on the development of exoskeletons bringing support to the user's joints to improve their gait and to help regaining independence in daily life. One example is Xosoft, a soft modular exoskeleton currently being developed in the framework of the European project of the same name. On top of its assistive properties, the soft exoskeleton will provide therapeutic feedback via the analysis of kinematic data stemming from inertial sensors mounted on the exoskeleton. Prior to these analyses however, the activities performed by the user must be known in order to have sufficient behavioral context to interpret the data. Four activity recognition chains, based on machine learning algorithm, were implemented to automatically identify the nature of the activities performed by the user. To be consistent with the application they are being used for (i.e. wearable exoskeleton), focus was made on reducing energy consumption by configuration minimization and bringing robustness to these algorithms. In this study, movement sensor data was collected from eleven stroke survivors while performing daily-life activities. From this data, we evaluated the influence of sensor reduction and position on the performances of the four algorithms. Moreover, we evaluated their resistance to sensor failures. Results show that in all four activity recognition chains, and for each patient, reduction of sensors is possible until a certain limit beyond which the position on the body has to be carefully chosen in order to maintain the same performance results. In particular, the study shows the benefits of avoiding lower legs and foot locations as well as the sensors positioned on the affected side of the stroke patient. It also shows that robustness can be brought to the activity recognition chain when the data stemming from the different sensors are fused at the very end of the classification process.**

Keywords: Stroke, Exoskeleton, IMMUs, Activity Recognition Chain, Sensor reduction and position, Robustness

I. INTRODUCTION

Many people after a stroke suffer from a variety of gait impairments like drop-foot or stiff-knee gait. These have a negative influence on performing daily life activities, leading to a reduction of their health and quality of life [1, 2]. Helping patients to regain proper mobility after a stroke has been, and still is, a major goal in stroke-rehabilitation.

Assistive devices like wheelchairs, canes or ankle-foot orthoses are often used after stroke to improve mobility and independence in daily life. These so-called passive devices allow patients to compensate for their disabilities but not to restore their gait pattern [3]. Active therapeutic devices, such as robotic gait trainers, have been designed and implemented to actively support the patients' gait rehabilitation, in an attempt to efficiently improve mobility. Following the principle of *'assistance as needed'*, these devices provide support to the different joints (hip, knee and ankle) at the appropriate time during gait of an individual. Successful examples of such devices are *Lokomat* [4] and *LOPES* [5], which are both used in clinical settings with the patient walking on a treadmill.

More recently, active assistive devices like *ReWalk* [6] and *EksoGT* [7] were developed, allowing a patient to walk in "the real world", without the constraint of a treadmill or a lab setting. However, these exoskeletons are still often used with guidance of a clinician. Moreover, they have a rigid structure, a heavy weight and a bulky design. This limits the independent use during daily life activities and in the home environment. Combining power supply longevity and actuators efficiency in an everyday wearable lightweight device represents a huge challenge that the scientific community is still facing.

The European project *XoSoft* (H2020) aims at taking this challenge by developing a soft modular exoskeleton intended to bring specific solutions to assist people with mobility impairments in both clinical and home settings. The exoskeleton is furthermore equipped with inertial and magnetic measurement units (IMMUs) to monitor the user's kinematics. The analysis of this data would facilitate a better follow-up of the user's rehabilitation to healthcare professionals and the users themselves, e.g., performance analysis and trend analysis. It would also help to improve safety, e.g., fall and abnormal behavior detection. However, prior to carry-out these analyses, the nature of the activities performed by the user must be known. Without the behavioral context, it is fairly difficult to interpret the lengthy and detailed data files of body segment and joint kinematics stemming from the IMMUs.

To provide this context, an automatic Human Activity Recognition method (HAR) based on IMMU data is used. A common way of achieving HAR is to implement an Activity Recognition Chain (ARC), which consists of signal processing and machine learning techniques [8]. Besides the common issues linked to HAR, such as the definition and diversity of physical activities, the context of soft modular exoskeletons brings in two other challenges: the minimization of the energy consumption and the robustness to sensor failures.

To assure the exoskeleton a certain autonomy, it is required to preserve battery use as much as possible. For example, for one day of independent use, activities have to be monitored continuously while actuation is not always required. In this case, one way of reducing the energy consumption of the recognition system is to use a reduced amount of IMMUs. The fewer the sensors used, the less power to be supplied, and the longer the battery life is. However, given the large variety of impairments inside the post-stroke population, finding the proper combination of sensors in terms of number and location on body is not obvious. In previous similar studies, waist [9], shank [10] and foot [11] were the main locations where the sensors were positioned on patients, irrespective of the kind of impairments. To our knowledge, no systematic approach in stroke patients has been performed for finding the relationship between sensor

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configuration (number & location) and classification performance. It is furthermore unknown how the side affected by the stroke influences this relationship. The first part of this study aims at addressing these two questions.

Technological anomalies are likely to occur when the exoskeleton is worn on a daily-basis. In particular, the IMMUs might be damaged, introducing some sort of noise into the signals, e.g., data loss, electronic noise and signal drift [12]. When a soft modular exoskeleton is used in a home setting, regular checks of the sensors state are not possible. Therefore, the ARC must be robust enough to keep the same level of recognition accuracy. This characteristic of the ARC is also addressed in this study.

All in all, this paper aims at shedding new light on how activity in stroke patients can be detected offline in the context of a wearable exoskeleton, considering energy consumption reduction and robustness. The contributions of this work are the following:

- We collected lower body and trunk kinematics data with a wireless IMMU system for eleven stroke survivors while performing six locomotive activities.
- We implemented two machine learning HAR models, differing on how and where in the ARC the data from the different sensors is combined, i.e. before (feature fusion) or after (decision fusion) the classification.
- We evaluated the influence of reducing the number of IMMUs on the models' performances for both user-dependent and user-independent scenarios.
- We provided hints on where to locate the IMMUs on stroke survivors' bodies considering the amount of sensors and the affected side of the subject.
- We evaluated the robustness of the developed HAR models for both user-dependent and user-independent scenarios.

II. Method

A. Data Collection

The measurements were performed at Roessingh Research and Development, The Netherlands, and were approved by the local medical ethical committee (Medisch Ethische Toetsings Commissie Twente).

Subjects: Eleven stroke survivors (7 right, 4 left side affected), aged between 31 and 77 years, were included in this study. All subjects were able to walk without physical support of another person (Functional Ambulation Categories ≥3) [13]. Two subjects walked with a tripod cane and six used an ankle-foot orthosis.

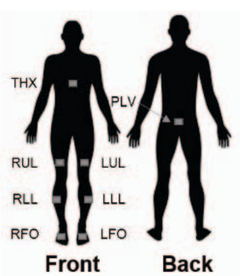

Figure 1: IMMU locations on body. THX: Thorax, PLV: Pelvis, RUL-LUL: Right/Left upper leg, RLL-LLL: Right/Left lower leg, RFO-LFO: Right/Left foot.

Material: The monitoring was done using eight IMMUs (Xsens MTw2 wireless motion trackers [14]) attached to the participant with Velcro straps at different locations (Figure 1). The signals were annotated during the measurements with a smartphone application delivering the time (in ms) and the name of the performed activities. A video camera was recording the measurements to provide an extra check.

Protocol: First, the subject was asked to assume a standard posture standing upright, facing north, for several seconds. The orientation data registered during this pose were used for segment calibration, which delivered the relationship between the sensor reference frame and the reference frame of the body segment it was attached to. The subject then performed five tasks reproducing main locomotive daily life activities. Each task started and ended in a seated position. The tasks one to four were repeated six times, while task five was performed five times. The tasks are described as followed:

- Task 1 - L-test: Describing an L while walking [15]
- Task 2 - Figure-of-8: Walking in a figure-of-8 pattern around two aligned cones.
- Task 3 - Side Steps: Turning 360° in place (left and right), and walking sideways (left and right)
- Task 4 - Daily Living Task: Opening/closing a door and moving objects from different tables (turns required).
- Task 5 - Stairs: Climbing stairs up and down.

B. Activity Recognition Chain

Approach: The activity recognition chain was designed in Matlab R2016b. To build the algorithm, the common steps in the human activity recognition field were followed [8]. All parameters of the chain were selected based on systematic analyses that were performed to determine the best values to use. Accelerometer data (x,y,z), gyroscope data (x,y,z) and magnetometer data (x,y,z) were used as input to the chain. The raw data, sampled at 100Hz, was first pre-processed to keep only frequencies corresponding to human gait [16]. A 2nd order low-pass filter (zero-phase Butterworth) with 7Hz cut-off frequency was applied on the calibrated signals. Subsequently, the signals were segmented into consecutives windows of 1 second with 50% overlap. Mean and standard deviation were extracted from each of these windows and given as input to the k-nearest neighbors classifier (k=1). The output of the chain consisted of a list of activities predicted by the classifier. Each predicted activity corresponded to a window. The labels describing the activity represented by each window were used for two purposes: during the training phase, they were fed together with the features vectors into the classifier; during the testing phase, they were compared to the predicted activities of the algorithm to assess its performance. Analyses were performed offline. Activities to recognize were the following: Sitting, Standing, Transition (sit-to-stand, stand-to-sit), Side-Steps, Stairs and Moving.

Feature fusion vs decision fusion: There are two main ways of dealing with multiple sensors in HAR. The data coming out of the different sensors can either be combined, or 'fused', before or after the classification step of the ARC. In the first case, the fusion occurs at the feature level after extraction. All the features are put together to obtain one unique vector which is then fed to the classifier (feature fusion, FFARC). Decision fusion ARC (DFARC) on the other hand, consists of multiple classifiers, one per sensor, of which outputs are then fused in order to obtain a unique prediction. Both techniques have their pros and cons. In

Figure 2: Composition of the different sensor configurations used in this study. The colours correspond to the bar colours in Figure 4.

ID n°	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41
THX	X								X						X	X	X	X	X								X	X	X	X	X				X	X		X	X		X
PLV		X							X											X	X	X	X	X			X	X	X	X	X				X	X	X		X		X
RUL			X							X			X		X			X		X			X		X		X			X		X	X		X		X	X	X	X	X
LUL				X						X				X	X				X	X				X		X	X				X	X	X			X	X	X	X	X	X
RLL					X						X		X			X		X			X		X		X			X		X		X		X	X		X	X	X	X	X
LLL						X					X			X		X			X		X			X		X		X			X	X		X		X	X	X	X	X	X
RFO							X					X					X					X			X				X				X	X	X					X	X
LFO								X				X					X					X				X			X				X	X		X				X	X

particular, DFARCs are known to better deal with sensor defects than FFARCs [8, 12]. Both were implemented in this study. The Hierarchical-Weighted Classifier [12] is a decision fusion algorithm, which particularity lies in the existence of several layers consisting of classifiers and weighed decisions. The deeper layer consists of binary classifiers aiming at discriminating one specific activity from the others ('one-versus the rest') based on data from a unique sensor. The outputs of these classifiers are weighted by a set values calculated during training (sensitivity, sensibility) to get a unique prediction. These sensor predictions are then weighted as well by a second set of parameters also calculated during training. The application of these parameters to the different sensor outputs results in a unique final prediction.

User-dependent vs user-independent model: User-dependent (UD) and user independent (UI) denominations refer to the provenance of the data used for training the model. In the first case, the ARC is trained on the user data himself, preliminarily registered for this purpose. In the second case the ARC is trained beforehand on data from several other subjects. In this study, the analyses were done on both models. To assure the generalization of our models and prevent overfitting, we performed cross-validation in both cases. For the user-specific models, the k-fold cross-validation method was used, with k = 10. The Matlab function, *crossvalind,* was used to distribute the windows in the different subsets. For the user-independent models, the leave-one-out method was chosen.

Statistics: All results presented in this study correspond to the weighted F1-score (wF1). This dimensionless quantity, ranging from 0 to 1, allows to equally take into account the results from each class [17]. It is calculated as follows:

$$wF1 = \frac{2}{Nw\ total} \sum_{i=1}^{Nact} Nw_i \times \frac{precision_{\ i} \times recall_{\ i}}{precision_{\ i} + recall_{\ i}}$$

Where Nw represents the number of windows in the dataset, for all activity types ($Nw\ total$) or for a specific activity type (Nw_i). $Nact$ is the number of activity types, in this study $Nact$ equals six. Precision is the number of true positives (TP) divided by the sum of TP and false positives (FP). Recall is defined by the division of TP by the sum of TP and false negatives (FN).

Calculations and Figures were based on the individual performance results in the case of user-dependent model; and on the cross-validation results in the case of user-independent model.

The analyses of statistical differences, in Figure 4 and in section III, were performed in Excel 2016, with the two-tailed T-test assuming unequal variances (α = 0.05), because the sample sizes are rather small and the variances are not known.

The confidence intervals in Figure 3, 4 and 5 were calculated in Excel 2016. The confidence level was set to 95%.

The boxplots of Figure 3 were computed with Matlab R2016b.

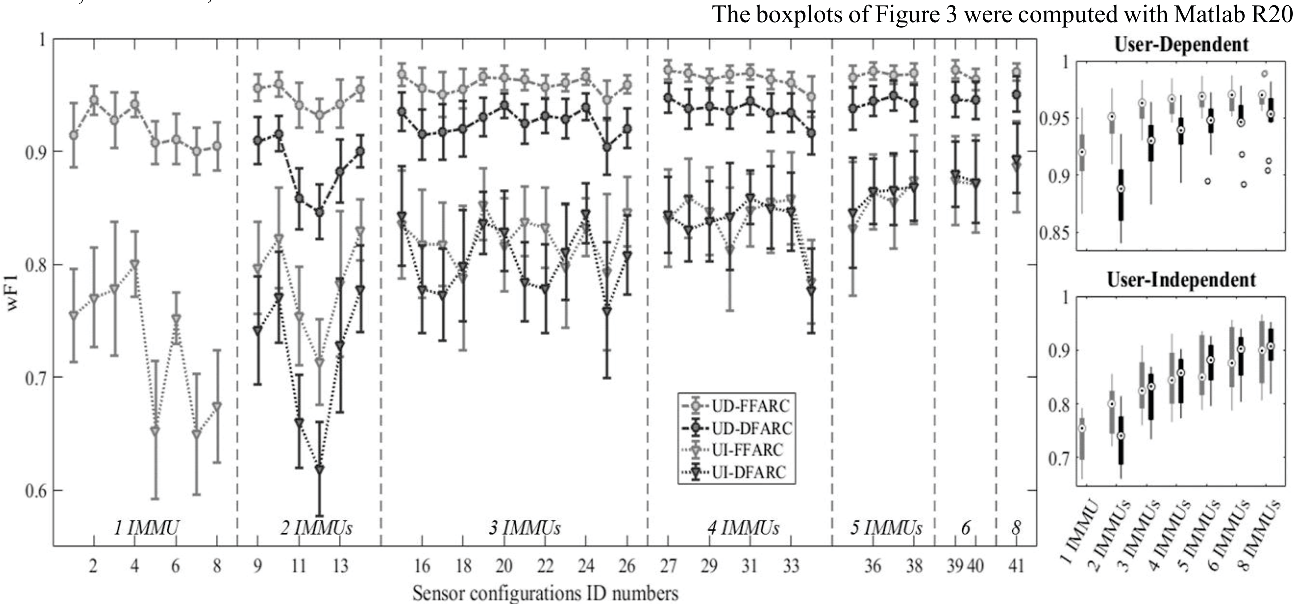

Figure 3: Performance results of the four ARCs; for each sensor configuration detailed in Figure 2 (left); and for configurations grouped per number of IMMUs (right). Left: The average of the wF1 over all subjects and their 95% confidence intervals (Excel 2016) are represented in this plot. Right: The boxplots were compiled via Matlab R2016b based on all the wF1 from the different subjects obtained with the different configurations containing a given number of sensors.

C. Sensor configurations

Forty one sensor configurations were selected among the large amount of possibilities (Figure 2). For the DFARC, only the configurations with at least two sensors were evaluated, reducing the number of configurations to thirty-three. Two main kinds of configurations were included in this study, i.e., symmetric and asymmetric configurations. The first one included sensors positioned on the same limbs from both legs while the second contained sensors from one side only (right or left). This choice was motivated by our goal to discover the relationship between sensors' position on the body and the affected side of patients.

D. Robustness

To evaluate the robustness of our ARCs, we simulated a failure in the signals coming from the IMMUs. All three channels (x,y,z) from the accelerometer were replaced by zero values to mimic an out-of-battery situation. The ARCs were run nine times, where each time an additional sensor encountered the failure, in order to evaluate the limits of the robustness of the ARCs i.e., from no IMMU affected to all IMMUs affected. The IMMUs were affected following an order selected randomly but identical for the evaluation of each ARC. For both user dependent and independent models, only the data used for the testing was affected by the failure.

III. Results

A. Sensor configuration

1) IMMU number reduction influence:

Reducing the amount of IMMUs decreases the recognition performance of all the four ARCs, i.e., UD-FFARC, UD-DFARC, UI-FFARC, and UI-DFARC. However, in the case of the user-dependent model (Figure 3, right), the decrease of performance occurs when less than three sensors are used. Using more than three and four sensors shows a minimal increase of the performances in FFARC and DFARC respectively as suggested by the plateau on Figure 3, right. There is indeed no longer significant difference between the different categories. Indeed, in FFARC the p-value between the use of three IMMUs and the use of eight equals 0.07. In DFARC, the p-value between the use of four IMMUs and the use of eight equals 0.06. Moreover, we observe that the decrease of the performance is accompanied by an increase of the variance inside a category. Both FFARC and DFARC follow this trend, but DFARC results in lower wF1 values and bigger variances inside each category, and in particular, when less sensors are used.

In the case of user-independent model, the plateau is less pronounced. The increase is no longer significant from four IMMUs in the case of FFARC (4-8: p-value = 0.16) and from five IMMUs in the case of DFARC (5-8: p-value = 0.16). Contrary to what is observed in the user-dependent model, FF and DF ARCs reach the same level of performances when three or more sensors are used and both show bigger variances inside the different category than in UD. We also observe no significant reduction of the variance when the number of sensors used increases. All results are lower in the user-independent than in user-dependent models.

2) IMMU on body location influence:

In both user-dependent FF and DF ARCs, the performance curves describe the same trend (Figure 3, left). To be able to state whether or not a specific configuration shows good performances, the corresponding median value depicted in Figure 3 (right) was used as reference. We observe a decrease of the wF1 value when sensors from lower legs and foot are used (e.g., 11, 12, 16, 17, 21, 22, and 34) or when only sensors from the right leg are used (e.g., 13, 18, 25 and 30). The gaps between the performances from one configuration to another seem bigger in case of DFARC. The single-sensor configurations indicate that the PLV, THX, RUL, and LUL sensors provide better results. In general, though, the performances do not vary much when using diverse locations on body as long as three sensors are used, in particular when using FFARC. Moreover, the confidence intervals are rather small and become smaller when more sensors are used.

The performance gaps between the different configurations in user-independent models are more pronounced. The confidence intervals are also bigger than in user-dependent models and do not decrease when more sensors are used. However, the trend remains more or less the same except when three sensors are used. Indeed, the decrease of performance linked to the use of a majority of sensors coming from the lower limbs (i.e., lower legs and foot) is more pronounced in the case of DFARC than FFARC (e.g., 16, 17, 21, 22, 28 and 29). The performance gaps are also bigger between left and right configurations (e.g., 18/19, 23/24, 25/26). For the single-sensor configuration, upper body sensors also attain higher accuracies. However, the left lower leg (i.e., 6) in this setup performs almost as good as the upper body sensors (wF1 = 0.752), although below the median value (median = 0.755).

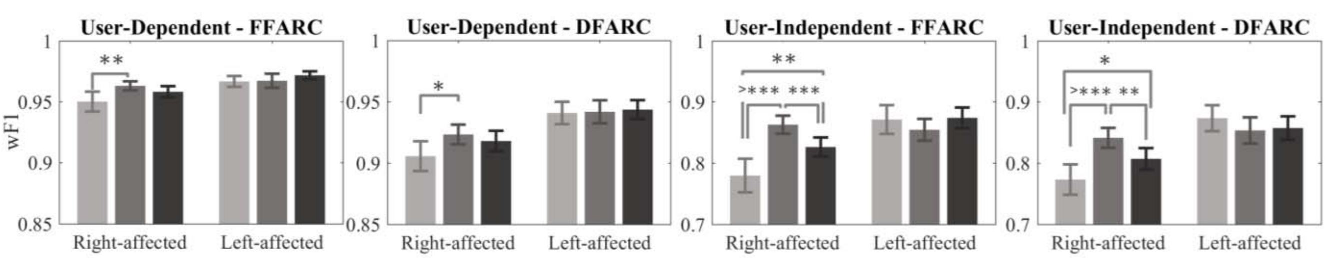

Figure 4: Performance results of the four ARCs, grouped according to subjects' affected side and configuration type. The average of the wF1 from both subjects' groups, obtained with the different types of configurations detailed in Figure 2; and their 95% confidence intervals (Excel 2016) are represented on these figures. The test used for significance assessment is explained in section II.B.

B. Subject affected side influence

To better understand the relationship between sensor configuration and affected side, the performance results were averaged over two groups of patients, i.e., the left-affected subjects and the right-affected subjects. For both groups, the wF1 values were divided into three groups (Figure 2), i.e., values obtained using sensors from the right leg (light grey), left leg (grey) or both legs (dark grey). In view of previous results in section III.A, we decided not to include configurations containing both foot sensors in this analysis. Their inclusion would have indeed biased the conclusions by lowering the results from the symmetric configurations. The results are presented in Figure 4. The first observation is the difference of performances between the two groups. Left-affected subjects show higher wF1 values than right-affected subjects. In user-independent setups (C, D), we note a small decrease of performances when using sensors from the affected side in the left-affected patients. However, this trend is not confirmed as for all four ARCs, no statistical difference is observed between the three different groups of sensors used. On the contrary, inside the right-affected group, the use of sensors from their healthy leg give significant higher results in all cases (A, B, C, and D). Moreover, in all four cases, the use of sensors from both legs give performances ranging between the two asymmetrical configuration groups. Only in the graph D, the p-values show that the performances attain with symmetrical configurations are closer to the one obtained with sensors from the affected side.

C. Sensor failure

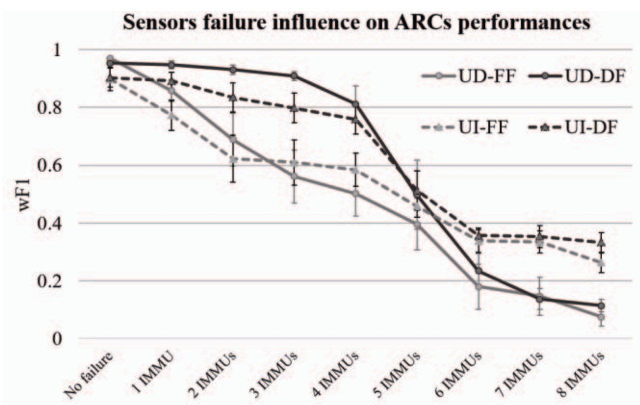

Figure 5: Performance results of the four ARCs when a certain number of sensors is affected by a failure. The average of the wF1 from all subjects and their 95% confidence intervals (Excel 2016) are represented on this figure.

As could be expected, the performances of the ARCs decreases when IMMUs encountered failures in both user dependent and independent setups (Figure 5). However, we observe a clear distinction between feature fusion and decision fusion ARCs. Statistical differences of means were evaluated between the performances obtained when no failure and when one failure occur. When one sensor is affected, the performance of DFARC stays the same as when there is no failure (UD: p-value = 0.55, UI: p-value = 0.59). In FFARC on the other hand, the performances drop significantly (UD: p-value = $4.42e^{-5}$, UI: p-value = $4.86e^{-4}$). The distinction between FFARC and DFARC increases and persists until four IMMUs are affected (wF1 equals ~0.6 and ~0.8 respectively). When five IMMUs are affected, both FF and DF ARCs drop to the same performance. When more than five IMMUs are affected, all performances are low, though there is a noticeable difference between user–dependent and user-independent model (wF1 ~0.15 and ~0.3 respectively). The confidence intervals are also rather small in the case of UD-DF till 3IMMUs are affected compared to the other 3 curves.

IV. Discussion

A. Sensor configuration

Figure 3 suggests that the reduction of the number of sensors while ensuring a decent level of accuracy is possible for activity recognition in stroke survivors. Depending on the type of ARC and model used, there is a limit beyond which the position of the sensors on the body have to be more carefully selected. This limit varies according to the kind of ARC and model used, from five to three sensors.

Since the user-dependent ARCs are trained to recognize the specific way of moving of the subject, these ARCs are less sensitive to the reduction and the position of the sensors. For both FF and DF ARCs, using user-dependent models allow to reduce the number of sensors of one more than when using user-independent models before reaching the limit beyond which the sensor position matters. The same difference is observed when using FFARCs compared to DFARCs.

According to Figure 3, two kinds of configurations are to be avoided to keep the performances high. The first one concerns the configuration containing sensors from the lower legs (LLL, RLL) and feet (LFO, RFO). This can be explained by the fact that these limbs have more freedom of movement than the upper legs, which are attached to the hip. Having more freedom of movement lead to more variability in the movement of the legs from subject to subject. This variability is even higher when dealing with people with impairments. The second kind of configuration to avoid seems to be the asymmetrical ones including sensors from the right limb. No logical explanation can be drawn from the analysis performed on the average data of all patients (Figure 3), hence our wish to go further by dividing the patients into two groups according to the side of their disability (Figure 4).

B. Subject affected side influence

When looking at Figure 4, it gives us the impression that left-affected subjects reach higher performances than the right-affected ones. Moreover, the selection of the sensors seems not to have any significant influence on the results from this group. These differences might be explain by the difference in the level of impairment of each patient. Given the information we have, it seems that the right-affected group contains more severely affected subjects (e.g., S04, S08). This would imply that the severity of impairments is also to be taken into consideration when choosing where to locate the sensors on body. However, this must be confirmed by further measurements with a clear differentiation in patient disability level. For the right affected group, the position of the sensors on body have a significant influence on the results, and the best performances are reached using sensors from the healthy leg. However, depending on the application, the selection of the location of sensors is not always tailor made. Using a symmetric configuration seems to provide a halfway solution between the two asymmetrical configurations. These findings contradict the conclusions drawn in [10], whose authors claim to have better results by combining sensors from both legs. Based on our results, the affected side seems indeed important to be taken into account when using a reduced amount of sensors, in particular when user-independent models are used.

C. Sensor failures

The results from Figure 5 suggest that, despite a small decrease of performances in user-dependent model, DFARCs are more robust than FFARCS as they can keep the same level of performance despite encountering a sensor failure. We can imagine that this would be a great asset if circumstances do not allow fixing or replacing the defected sensors right away. Again, the choice for one ARCs against the other all depend on the application they are implemented for.

D. Limitations of the study

Despite the good results we obtained, this study is subject to some limitations. The number of subjects, the use of an ankle-foot orthosis or not, and the balance between right and left affected groups limit the generalization of the conclusions. In order to verify the trend showed in this paper, experiments with a larger number of subjects should be performed. Moreover, the side of the affected leg is an important criterion to study to determine where to position the sensors. However, the nature of the impairment, like drop-foot or stiff-knee gait, should also be studied as it might influence the results as well. The configurations investigated in this study consist of a small sample of the numerous possible configurations. More should be evaluated, in particular asymmetrical ones. Moreover, the possibilities offered by the Hierarchical-Weighted Classifier are not completely explored. The algorithm offers indeed the possibility to select, for each sensor, different nature of features to fit the data perfectly. This might give higher performance results if the features are fine-tuned. Finally, the sensor failure evaluation was done as a proof-of-concept but it might be interesting to investigate the effect of different kind of failures on the ARCs.

V. Conclusion

This study showed the influence of sensors reduction and sensors failure on the performances of four activity recognition chains in stroke survivors. Reliable activity classification was possible for all subjects included. As every application is different, this study did not intend to state what is best to use but to give hints about what to be aware of when dealing with sensors selection and positioning in stroke survivors. The finding suggests that it is possible to reduce the amount of sensors, while keeping high performance results to a certain limit. Depending on the kind of ARC used, beyond this limit, it seems more important to select carefully where to locate the sensors on body. In this case, the study suggests avoiding the inclusion of sensors from lower limbs and foot, and positioning the sensors preferably on the non-affected leg of the subject. This is particularly important in user-independent models. Moreover, in order to bring robustness to the system, it seems wiser to use decision fusion ARCs, as it better deals with sensor failures.

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