Activity-aware essential tremor evaluation using deep learning method based on acceleration data

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ABSTRACT

Background: Essential tremor (ET), one of the most common neurological disorders is typically evaluated with validated rating scales which only provide a subjective assessment during a clinical visit, underestimating the fluctuations tremor during different daily activities. Motion sensors have shown favorable performances in both quantifying tremor and voluntary human activity recognition (HAR).
Objective: To create an automated system of a reference scale using motion sensors supported by deep learning algorithms to accurately rate ET severity during voluntary activities, and to propose an IOTA based blockchain application to share anonymously tremor data.
Method: A smartwatch-based tremor monitoring system was used to collect motion data from 20 subjects while they were doing standard tasks. Two neurologists rated ET by Fahn-Tolosa Marin Tremor Rating Scale (FTMTRS). Supported by deep learning techniques, activity classification models (ACMs) and tremor evaluation models (TEMs) were created and algorithms were implemented, to distinguish voluntary human activities and evaluate tremor severity respectively.
Result: A practical application example showed that the proposed ACMs can classify six typical activities with high accuracy (89.73%–98.84%) and the results produced by the TEMs are significantly correlated with the FTMTRS ratings of two neurologists ($r_1 = 0.92$, $p_1 = 0.008$; $r_2 = 0.93$, $p_2 = 0.007$).
Conclusion: This study demonstrated that motion sensor data, supported by deep learning algorithms, can be used to classify human activities and evaluate essential tremor severity during different activities.

1. Introduction

Essential tremor (ET) is one of the most common neurological disorders affecting 4.6–6.3% of adult above the age of 60–65 [1]. It mainly affects the upper limbs with the consequent interference in basic activities of daily living [2]. Tremor analysis during daily living is crucial in order to better understand the patient status and to evaluate treatment effects [3]. In clinical practice, ET is usually assessed by several tremor validated rating scales [4–6]. Although, these rating scales have demonstrated clinical utility, they require the presence of a clinician for scoring. Their results are subject to clinical judgment and show significant intra and inter explorer variability and cannot reflect tremor fluctuation patterns throughout the day during different daily activities [3,7].

ET shows a frequency between 4 and 12 Hz, which is higher than the frequency of normal voluntary human movements [8,9]. The feasibility of detecting and evaluating tremor using motion sensor data has been proved [3,10,11]. The development of wearable technology provides a convenient method to collect motion data. The study presented in Ref. [12] has verified the practicability of using a smartwatch to analyze and diagnose tremor and the study of [13] demonstrated the feasibility of continuous monitoring of ET for long period during daily activities.

Most ET patients show both kinetic and postural tremor [1] and the severity of tremor varies when patients conduct different activities [3,14,15]. The tremor evaluation methods based on motion sensors presented in most of previous studies, like [12,13], only focused on the tremor itself without considering the background activities. The evaluation results produced by those methods cannot reflect the tremor fluctuation among different daily activities. Because of such variability and the scarcity in available datasets, the research in this field remains limited.

Deep learning is a paradigm of machine learning that enables computational models to learn representations of data with multiple levels of abstraction [16]. Many studies have proved that the use of deep learning can improve performance in a range of applications [16–18]. As a powerful feature extraction mechanism, deep learning has also been applied to human activity recognition (HAR) and achieved satisfying performance [19,20].

In addition, the blockchain technology brings the capability to keep public records of data, including the encrypted id of the patient to preserve anonymity, enabling to build up a system helping the research.

The goal of this study is to demonstrate the feasibility of using the acceleration data supported by deep learning algorithms, not only to recognize typical human daily activities, but also to accurately rate tremor severity during each specific activity in an automatic way. In addition, it aims to propose a blockchain like solution based on IoTA (Internet of Things Application), capable of sharing anonymous patient related tremor data helping to consolidate the research. Blockchain is a continuously growing list of records, called blocks, which are linked and secured using cryptography. Each block contains a cryptographic hash of the previous block, a timestamp, and transaction data. The utility of blockchain in our context is to provide trust and common understanding of data without dependences form a central authority or specific hardware. IoTA allows to implement cost free transactions with easier trust schema.

2. Material and methods

This study is approved by the ethics committee of the Getafe University Hospital (Madrid, Spain) and is conducted in accordance with the Declaration of Helsinki of the World Medical Association. All participant patients have signed an informed consent.

2.1. Subject

Twenty patients with essential tremor, 11 males and 9 females, mean age 63.0 ± 13.5 years (range 38–81) and tremor evolution time 10.35 ± 7.09 years, were include. All showed tremor in both upper limbs with different tremor leves, 4 of them associated cephalic tremor. The 75% of the patients had a family history of ET. None showed tremor of rest. Finally, in 3 a single-photon emission computed tomography using I-ioflupane was performed to exclude other types of tremor due to some atypical clinical characteristics. Eleven were under tremor therapy, two with primidone, six with propranolol, one both drugs, and two with clonazepam. Medication for ET was maintained during the experiment.

In order to compare the data five healthy subjects, mean age years 36.4 ± 10.3 (range 28–54), 3 males and 2 females, were included.

2.2. Procedures of experiment

The standardized experiment was designed on the basis of the Fahn-Tolosa Marin Tremor Rating Scale (FTMTRS) tasks that evaluate upper limbs tremor severity. The repetition numbers of the tasks were mainly based on the duration time of each task and each repetition. The target was to keep the overall duration of each task more or less the same while considering the body conditions of the patients to avoid muscle fatigue. Under the supervision of at least two neurologists, and wearing the watch firmly on the more affected wrist, patients perform the standardized tasks guided by a video.[1] The tasks include:

A1) Keep both arms horizontally extended for 20 s and then relaxed on the lap for 10 s. This task is repeated three times.
A2) Repeat the finger-nose test (touching the nose with the index

finger with the arm raised to 90°) 10 times, and then keep the hands relaxed on the lap for 10 s. This task is repeated twice.
A3) Write "THIS IS A SAMPLE OF MY WRITING″, and then keep both hands relaxed on the lap for 10 s. This task is repeated three times.
A4) Draw a large and a small spirals, and three lines sequentially with a 10-s rest between every two drawings. This task is repeated twice.
A5) Pour a full glass of water into another empty cup and then pour back for three times, and then rest for 10 s. This task is repeated three times.
A6) Simulate the action of drinking a full glass of water five times and then resting for 10 s. This task is repeated twice.

More details are available in the instructional video[1].

The experiments were videotaped for subsequent analysis and tremor scoring by two neurologists in a blind way. Each item was rated on a scale from 0 to 4 (no tremor to severe).

2.3. Hardware and software

A portable human movement monitoring system has been previously developed [21]. This three-layer system is composed of a smartwatch, which contains a tri-axis accelerometer and Bluetooth 4.0, for recording the user's arm movement data; an Android smartphone for receiving data from smartwatch and uploading them to a remote server; and a cross-platform document-oriented NoSQL MongoDB database on remote server for data storage and analysis. The information collected using this system includes three-axis arm movement acceleration values. The feasibility of analyzing tremor using data collected from a smartwatch has been validated in a previous study [22].

All movement data were recorded with frequency of 25 Hz and uploaded to the remote server in real time. Fig. 1 shows an example of the acceleration data over time during the experiment of an ET patient. Since rest tremor is not habitual of ET [3] and was not found in our subjects, it was excluded and treated as noise. As shown in Fig. 1, we define three components of the raw acceleration data. The six standard activities (A1 – A6) are individually considered as pure actions. There are gaps between those activities, which are defined as the remaining part of the signal between two pure activities, including the resting periods and other noises during the experiments. Transit means the transition between a pure activity and a rest section.

The target of this study is to identify the pure activities from the raw signal by activity classification models (ACMs) and classify them into different tremor levels with tremor evaluation models (TEMs). Fig. 2 demonstrates the proposed framework for activity classification and tremor evaluation.

All data preprocessing and model training in this study were implemented with a computer equipped with a 4-core Intel Core i5-4460 3.2 GHz CPU and a 12 GB of RAM memory. The operating system is Ubuntu Linux 16.04 64-bit version.

Data preprocessing is performed with RStudio. The deep learning model training and testing are conducted with TensorFlow (Version 1.0) and the model was built in Python (Version 2.7) language. TensorFlow (TF) is an interface for expressing machine learning algorithms, and an application for executing such algorithms, including training and inference algorithms for deep neural network models [23]. More specifically, the TF.Learn module of TensorFlow was adopted for creating, configuring, training and evaluating the deep learning model. TF.Learn is a high-level Python module for distributed machine learning inside TensorFlow. It integrates a wide range of state-of-art machine learning algorithms built on top of TensorFlow's low level APIs for small to large-scale supervised and unsupervised problems [24]. The complete code of data preprocessing with RStudio and building deep learning models with TensorFlow are provided in Appendix 1 of the online version.

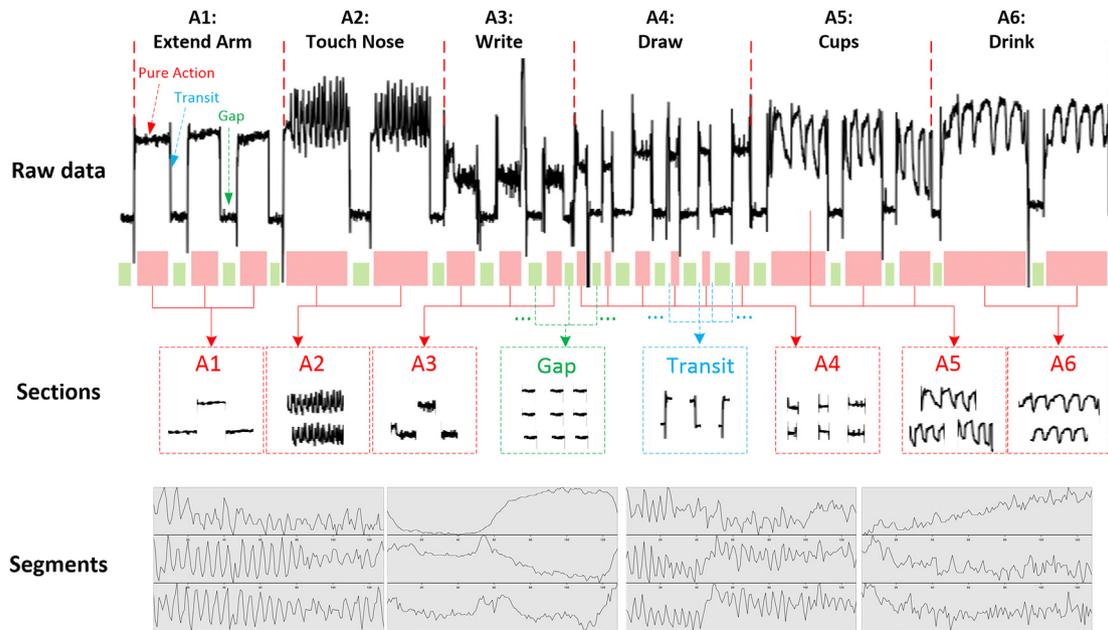[1] Available online: https://www.researchgate.net/publication/325923937.

Fig. 1. Example of raw acceleration data and the segmentation process.
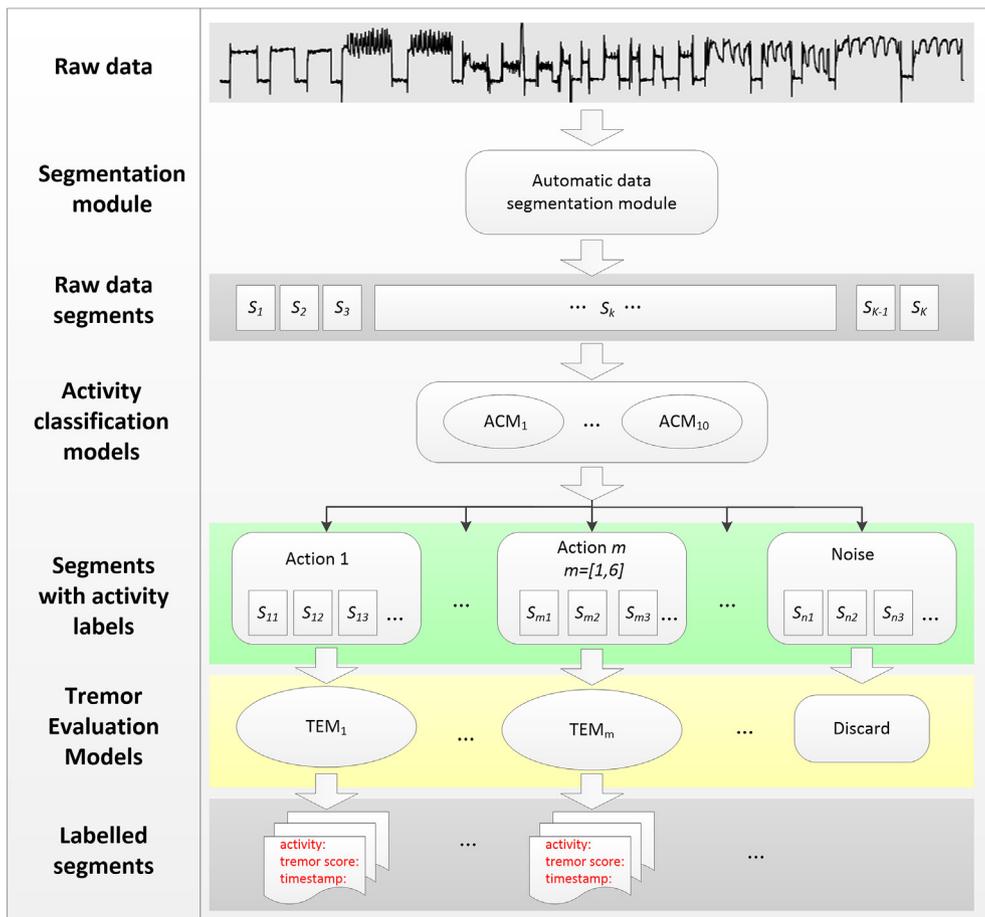

Fig. 2. The proposed framework for activity classification and tremor evaluation.

The IoTA system is an open source permission less public distributed ledger that utilizes a novel invention, called a "Tangle", at its core [25,26]. The Tangle is a new data structure based on a Directed Acyclic Graph (DAG). Each participant in the network that wants to make a transaction has to actively participate in the consensus of the network by approving the two past transactions. This attestation ensures that the whole network achieves consensus on the current state of approved transactions, and it enables a variety of significant features like.

- *Scalability:* IOTA can achieve high transaction throughput thanks to

parallelized validation of transactions with no limit as to the number of transactions that can be confirmed in a certain interval

- *No Transaction Fees:* IOTA has no transaction fees.
- Decentralization: IOTA has no miners. Every participant in the network that is making a transaction, actively participates in the consensus. As such, IOTA is more decentralized than any Blockchain.
- *Quantum-immunity:* IOTA utilized a newly designed trinary hash function called Curl, which is quantum immune (Winternitz signatures)

We have used one light IoTA node from the public repository (https://iotanode.host/), and segments and labels have been encapsulated in transactions. Then, they have been submitted by the software module to the IoTA tangle in an automatic way.

2.4. Data preprocessing

Data preprocessing includes data labeling and data segmentation. The raw data collected during the experiments are without labels. In order to use them to train the classification models, these raw data need to be properly segmented and labeled with the following steps.

First, the raw data of each subject were roughly partitioned into 8 groups, including 6 pure activity groups, a transit group and a gap group as shown in Fig. 1. Each group contains several data sections (different from the data segments below) with their own labels. For example, in Figs. 1 and 72 data sections can be obtained, including 19 pure activity sections, 19 gaps and 38 transit sections.

Then, all of these data sections (except the transit sections) are equally segmented into small segments using the sliding window method, which is also known as overlapping window method. This method is used because it is able to handle transitions more accurately and produce more training samples [27]. Exceptionally, the transit sections are segmented with the same window length manually, because their lengths are too short to apply the sliding window method.

The segmentation method is presented below:

Suppose a data section A.

$A = \{v_1, v_2, ..., v_n\}$, where n is the length of the section and v_i represents the i_{th} data record in the signal and $v_i = \{x_i, y_i, z_i\}$, where x_i, y_i, z_i represents the acceleration values on the three directions of the movement.

A is segmented by a sliding window with length W, overlapping length R.

Then the kth segment can be represented by:

$S_k = [v_{(R*(k-1)+1)}, v_{(R*(k-1)+1+W)}]$, where S_k represents the segment data array and $k = \left[1, \ round\left(\frac{n-W}{R}\right)\right]$.

After the segmentation, the raw data will be separated into small segments and every segment contains the tri-axis acceleration data, an activity label and a tremor score label. Some examples of these segments corresponding to different activities are shown on the bottom of Fig. 1.

2.5. Model building

As shown in Fig. 2, two types of models, ACMs and TEMs, are built and trained. They are the key modules of the proposed system. In this study, the deep Convolutional Neural Network (CNN) architecture [16,28] is used to build both ACMs and TEMs. CNN is one of the most popular deep learning approaches, which utilize layers with convolving filters that are applied to local features. The capacity of CNNs can be controlled by varying their depth and breadth, and they also make strong and mostly correct assumptions about the nature of the data samples. Compared to standard feed-forward neural networks with similarly-sized layers, CNNs have much fewer connections and parameters and so they are easier to train, while their theoretically-best performance is likely to be only slightly worse [18]. CNN has been wildly applied and has produced satisfying results in a number of studies [29–31]. The general structure of ACM and TEM in our study is similar but the inputs and outputs are different.

For ACMs, the inputs are all the samples obtained during data preprocessing, including pure actions, gaps and transit segments and correspondingly, the outputs of ACMs are the 8 activity classes. As for the TEMs, only the samples obtained from pure action data are used as inputs while the gaps and transit segments are excluded. The outputs of TEMs are the tremor severity scores. Evaluation models for each pure action are built and trained separately.

2.6. System application

In practical application, the raw data of a new patient will be sequentially segmented with the same length as during training process, but without overlapping. Segmented samples will then pass through the prepared ACMs and be classified into 8 classes. Afterwards, samples which are classified as pure activities will pass through their corresponding TEMs and be classified into different tremor levels. In the end, samples classification results which belong to the same pure activity will be summarized to reflect tremor severity during corresponding activity.

3. Results

3.1. Data segmentation

The data of 5 patients were selected for validation during the application step and the rest were used to train classification models. During data segmentation process, several segment lengths were used, including 2.56 s (64 data samples), 5.12 s (128 data samples), 7.68 s (192 data samples) and 10.24 s (256 data samples). Theoretically, the classification accuracy will be higher with longer segments. However, in some activities in our experiment, the duration is very short, for example, the spirals drawing (less than 10 s). In this case, long segment may cover more than one activities and resulting in misclassification. Therefore, the segment length 5.12 s (128 data samples) was adopted for further model training and applying.

3.2. Activity classification result

The 10-fold cross-validation method was used to train both the ACMs and TEMs. All segmented data samples were separated into 10 parts randomly and equally. During each training round, one of these 10 parts was selected as validation data and the rest as training data and then started a new round until all parts have been used once as testing data.

For the training of ACMs, 6640 samples were produced with the sliding window method during the segmentation process. The segment length was 5.12 s (128 data samples) and the overlapping length was 1.28 s (32 data samples). For the training of TEMs, 5630 samples were generated based on the pure activity data using the same segment and overlapping lengths as ACMs. More specifically, the sample numbers for the 6 activities (A1 – A6) were: 920, 840, 990, 580, 1300 and 1000 respectively. The maximum, minimum and average accuracies obtained by the 10-fold ACMs and TEMs are presented in Table 1.

As shown in Table 1, the proposed ACMs could recognize most of the predefined activities with high accuracy (mean 0.95 ± 0.03 SD). The proposed TEMs also produced high accuracy for tremor severity evaluation (mean 0.90 ± 0.06 SD).

In order to compare performance of tremor classification between the proposed activity-aware models and the traditional non-activity-aware based models, the samples of all 6 activities were mixed up and used to train tremor classification models without considering activity differences. As shown in Table 1, tremor classification accuracy based

Table 1
Classification accuracies obtained by ACMs and TEMs during the training process (A1: extend arm; A2: touch nose; A3: write sentences; A4: draw spirals; A5: pour water; A6: simulate drinking).

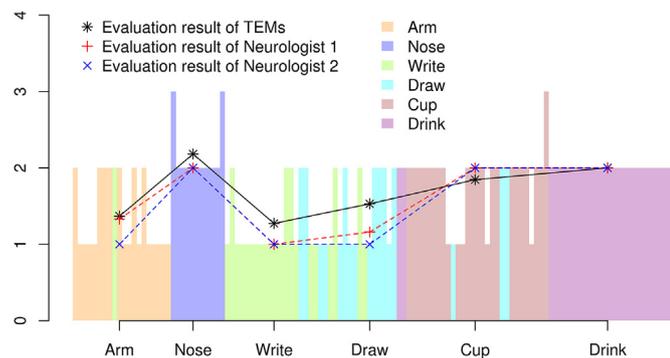|		A1	A2	A3	A4	A5	A6	Mixed
ACM	Max	0.9819	1.00	0.9956	0.9597	0.9282	0.9772	–
	Min	0.9191	0.9725	0.9703	0.8170	0.8137	0.9288	–
	Average	0.9632	0.9884	0.9811	0.9301	0.8973	0.9510	–
TEM	Max	0.9674	0.9643	0.9900	0.8966	0.8855	0.9806	0.8952
	Min	0.8913	0.8929	0.9091	0.7719	0.5846	0.9029	0.7890
	Average	0.9315	0.9440	0.9404	0.8564	0.8030	0.9517	0.8544

Fig. 3. Tremor evaluation results of one patient obtained by TEMs and two neurologists (the vertical axis represents tremor grades and the horizontal axis represents the action segments.).

on every single activity except A5 (Pour water, above 0.86) is higher than general accuracy when mixed up all activities (0.85).

3.3. Application result

Data from the same 5 patients were excluded during the model training process and used to verify the performance of the trained models in the practical application. These data were segmented into segments with the same length as in the model training process, 5.12 s (128 data samples). The 10 ACMs trained before were applied to these segments and classified them into 8 classes. The activity classification results during practical application were summarized on the basis of the outputs of the 10 ACMs. When there are different classification results for the same segment, the mode of the 10 results were adopted.

Based on the activity classification results, the segments which were classified as the 6 pure activities were used as input of the TEMs. These segments were classified into different tremor levels. For each segment, when classification results of the 10 TEMs were different, the mode statistic of the 10 results was adopted. Classification results of the segments which belong to the same data section (a continuous activity) were taken average to represent the score of this activity. Fig. 3 shows evaluation results of the six activities from one patient produced by TEMs and by two neurologists. The classified segments were plotted according to their original sequence in time domain. The activity classification results, which are produced by ACMs, are represented by six different colors and the tremor evaluation results, which are produced by TEMs, are represented by the height of the bars. The results show that the ACMs correctly recognized most of the activities, except that some "draw" segments were misclassified as "write". Significant correlations ($r_1 = 0.92$, $p_1 = 0.008$; $r_2 = 0.93$, $p_2 = 0.007$) were obtained between evaluation results produced by the TEMs and two neurologist's FTMTRS scores. Since each activity was repeated several times, the average FTMTRS scores of all repeats were adopted to compare with the TEMs results. The tremor level of different repeats for the same activity may differ according to the observation during the experiments and this is also verified by the neurologists' evaluations.

For example, the tremor level during the second repeat of the "arm" activity was higher than the first and third repeats. Correspondingly, the evaluation scores of these three repeats are 1, 2 and 1 respectively.

As a matter of convenience, one specific IoTA address to send all the transactions has been defined:'GEKMPUCSIRYYYNKLMFQDMJIIFAEJ-FHRUNWSATCMMLDNUBIIROAVPZVDSVOQBKCNVIOJKCRAPHO-YOR9YSZ'. Therefore, blocks can be retrieved from different locations and be decrypted to recover the underlying json data structure.

4. Discussion

This study proposed an accurate evaluation system of activity-aware ET. Compared with previous studies, we obtain a deeper level of tremor evaluation. The proposed system not only focuses on tremor itself, but also takes into account the background activities when tremor occurred. The deep learning techniques are used twice in the system to classify human activities and evaluate tremor. The proposed ACMs could recognize predefined human activities with high accuracy. The activity-aware tremor evaluation results show strong correlation with the ratings of the neurologists. This correlation is stronger than that obtained in previous studies [3,4,13], which didn't consider the impact of background activities. It means that the introducing of activity classification can increase the accuracy of tremor severity evaluation against the traditional non-activity-aware models.

The output of the proposed system is a sequence of blocks of information, where each block contains the timestamp, gender, age, a numeric identification (ID) making it possible to track the record in reference to the hospital clinic identification, as well as the action and its score according to FTMTRS. In order to foster the research about ET, this paper proposes to share the produced data blocks in a safety way, preserving anonymity. It has been decided to use blockchain like IOTA distributed ledger to share them. Therefore, a light server has been installed through Docker® technology, and blocks where encrypted and encapsulated using the benefits of Wallet and cryptocurrency. The central idea is to 'send' transactions where the value is 0, the tag refers to the ET topic and the hierarchical geography references.

The implemented IoTA solution gets benefit from the public tag that can be additionally used to attach identification for the Hospital and Country codes. In this way, researchers can share and access to wider ET related information, helping to understand individual evolution in both, short and long terms. Indeed, the direct and non-restricted access to such information can be seen as a driver for getting high consensus level as training dataset will be larger. Because of the proposed models are based on collected data, classifiers will improve their accuracy based on the increase of samples.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.parkreldis.2018.08.001.

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