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Reputation-Aware Data Fusion for Quantifying Hand Tremor Severity Form Interaction with a Smartphone

Tetiana BILOBORODOVA[a,c,1], Inna SKARGA-BANDUROVA[b,c,2], Igor KOTSIUBA[c] and Illia SKARHA-BANDUROV[d]
[a] *Volodymyr Dahl East Ukrainian National University, Ukraine*
[b] *Oxford Brookes University, United Kingdom*
[c] *Healthymity, United Kingdom*
[d] *Luhansk State Medical University, Ukraine*

Abstract. In this paper, we present an approach to improve the accuracy of hand tremor severity in Parkinson's patients in real-life unconstrained environments. The system leverages data achieved from daily interaction people with their smartphones and uses technologies for classifying and combining data. We describe the basic concept of data fusion and demonstrate how different combination techniques can improve the accuracy of tremor detection. The fusion enable to achieve the 23.5% improvement with respect to the average of individual classification models.

Keywords. Data fusion, hand tremor, Parkinson's disease

1. Introduction

Hand tremor is one of the common symptoms of neurological disorders, including essential tremor (ET), stroke, multiple sclerosis, traumatic brain injury, and neurodegenerative diseases such as Parkinson's disease (PD). Unlike some others, Parkinson's syndrome is characterized by resting tremors, which are weaker with movement and get worse at rest. It is often asymmetrical and can remain one-sided for a long time. Hand tremor typically has a negative impact on a person's daily activities but will not necessarily shorten the life span. For example, ET may progressively get worse but does not cause health problems, while untreated PD can reduce the quality of life to a significant extent. Distinguishing ET from PD tremor can be challenging, not only in the early stages of these diseases but also in severe stages since ET patients may develop a resting tremor, and patients with severe PD may develop an action tremor [1]. Laboratory testing, neurological and physical examination, outpatient diagnostics in hospital settings are the major sources of information for differentiating these two diseases. Accurate classification and recognition of the tremor degree is one of the first steps towards timely detection of the progression of symptoms of Parkinson's disease. As things dramatically changed, solutions for remote daily real-life monitoring become

[1] Inna Skarga-Bandurova, Visual Artificial Intelligence Laboratory, Oxford Brookes University, Wheatley Campus, Wheatley, Oxford, OX33 1HX, UK; E-mail: iskarga-bandurova@brookes.ac.uk..

in high demand. Dozens of systems and wearable sensors have been developed to monitor the daily PD progression and response to treatment of PD motor symptoms; however, most of them used special sensors that should be attached to the body to capture tremor and therefore have not been pervasive among PD patients. Another option is wearable-free systems that used smartphone sensors to measure tremor parameters in unconstrained environments. These solutions are also under development, and one of the main challenges here is the quality of classification.

This paper introduces the concept of data fusion for smartphone-based Parkinson's disease monitoring system [2]. Data fusion is a process of integrating data, technologies, methods and knowledge to improve data quality, reduce uncertainty, and extract new features. This is a broad umbrella term for various combination techniques and one of the major information support tools for the comprehensive assessment of symptoms in remote biomedical monitoring systems. It helps to reign in the influence of such data properties as outliers, inconsistency, multimodality, correlation, etc., on the results and to produce more accurate and useful information. Data fusion can be done at three levels, data level, feature level, and decision level. The study [3] investigates decision-level data fusion of the signals from sustained phonation and text-dependent speech modalities for Parkinson's disease. Signals were recorded through two channels simultaneously. Additional modalities were obtained by splitting speech recording into voiced and unvoiced parts. In [4], a non-obstructive monitoring and rehabilitation system for long term monitoring body posture and movement was discussed. The system uses the feature-level fusion of sensory data provided by a network of wireless sensors placed on the user's periphery. In [5], a multisensory decision fusion system has been presented with biometric and medical monitoring applications. This system includes an ECG sensor, a temperature sensor, an accelerometer, and provides distinctive haptic feedback patterns to the user health state. The paper [6] presents a smart distant monitoring system for Parkinson's and Alzheimer's patients and reveals valuable insights for early detection and prevention of events related to their health. This system involves data capturing and multimodal fusion to extract relevant features, analyze data, and provide useful recommendations gathers signals from the multisensory band (bracelet), binary non-intrusive sensor, RGB-D (Microsoft Kinect v2) camera, zenith camera, wireless sensor network anchors or beacons. Table 1 summarizes some of the features of the most representative studies on the application of sensor fusion in general health. Most of these studies fuse the features or decisions extracted from motion sensors and physiological sensors such as ECG, body temperature to remote monitor the health status of the individuals. However, none of them used smartphones in everyday life.

Table 1. Application of data fusion in motor and behaviour activity

Reference	Fusion level	Sensors
[3]	decision level	acoustic cardioid, smart phone microphones
[4]	data level feature level	accelerometer, gyroscope, magnetometer
[5]	decision level	accelerometer, ECG, temperature
[6]	feature level	multisensory band, binary non-intrusive sensor, RGB-D (Microsoft Kinect v2) camera, Zenith camera, wireless sensor network anchors

The recent studies proposed the practical application of smartphones in real-life environments [7] to detect hand tremor in people with PD, although tremor severity has not been discussed. Our study aims to extend previous studies in terms of system functionality and track PD symptoms outside of health care settings quantifying tremor symptoms. A data fusion approach is developed and used to assess the severity of Parkinson's disease symptoms.

2. Materials and Methods

The tremor detection module (TDM) runs in the background and uses the signals received from the smartphone's embedded accelerometer and gyroscope sensors to quantify PD hand tremor level. The recorded data are processed using statistics to create an initial hypothesis about the presence and severity of symptoms and transmitted to the data fusion module (DFM) that combines these data with results of the PD tests and historical data stored in the cloud. Based on the fusion results, the module generates a combined symptom score.

The DFM is based on reputation awareness fusion mechanism [8] and includes local classification models and a global data fusion model. The local model assumes that each piece of input data classified separately. The local classification model includes (1) smartphone sensor data, which provides input data for the classifier (2) the classifier, which is responsible for recognizing the severity of the symptom and determining whether each observation belongs to the severity class, and (3) the simulation result. The global pooling model uses the main results of the local model and uses voting based on several models, in particular, reputation models and majority voting. The purpose of data fusion is to assess the severity of Parkinson's disease symptoms accurately. The basic structure of data fusion in remote monitoring of symptoms of Parkinson's disease is shown in Fig. 1. Reputation awareness fusion leverages voting mechanisms to facilitate decision-making and filter resources based on their quality. Reputation voting is a post-classification data aggregation approach. When each classified case makes an individual decision about whether an instance belongs to a class, a consensus must be reached among the classified cases. Reputation systems use the ‘conditional transitivity’ property of trust, which implies that the more aggregated data about a source's reliability, the more likely that measurement is trustworthy in future calculations. Reputation-based voting approaches are based on ascertaining an individual's reputation classified observation and making decisions based on the classified observations that have the highest reputation. To make a judgment, each observation first sends its classification result, called the weight value, to all other observations in its environment. The weights are determined for all adjacent observations.

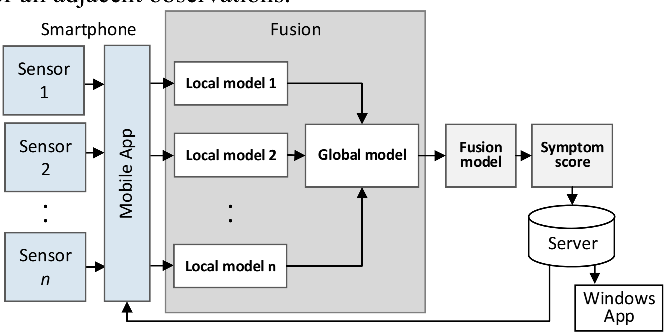

Figure 1. The structure of data fusion module.

Further, each observation judges other observations, considering itself as a standard. Judgment is achieved by comparing the difference between the weight of the case itself and other neighbouring classified cases. If the difference is less than the threshold θ (chosen based on context), the scored case gives a positive vote ($V_{new} = V_{old} + 1$) to other cases. Otherwise, the evaluated observation gives a negative vote ($V_{new} = V_{old} - 1$). The data obtained is used to reach a consensus between different observations. The first reputation-based method checks each individual's local reputation against other entities. The local reputation value is derived from the average V_i (positive or negative votes cast by other observations) for each classified observation. The average local reputation is then multiplied by the node weights calculated using Eq.1 to assign global reputation values. The highest reputation weight class is the result of the voting procedure.

$$w_i = R_i \times a_{ci} \tag{1}$$

where w_i denotes the reputation value of the classified observation i, R_i is the local reputation value of the classified observation i in terms of other observations, and a_{ci} is the weight of the classified observation i.

The second reputation-based method uses two thresholds θ_1, θ_2. Comparing local reputation values R_i with θ_1 and θ_2 indicates whether the classification performs well. If $R_i \geq \theta_1$, then the classified observations made perfect decisions, if $\theta_1 > R_i \geq \theta_2$, then the classified decisions are normal, and if $\theta_2 \geq R_i$, then the classified observations made the poor decisions. Standard quality thresholds are rated as 0.5 points for poor performance, 1 point for normal performance, and 2 for ideal classification performance. Based on these values, equation (2) is used to assign a reputation to each classified case.

$$w_i = S_i \times a_{ci} \tag{2}$$

where w_i denotes the reputation value of the classified observation i, a_{ci} is the weight of the classified observation i and $S_i = 2$ if $R_i \geq \theta_1$, $S_i = 1$ if $\theta_1 > R_i \geq \theta_1$, and $S_i = 2$ if $R_i \geq \theta_1$, $S_i = 0.5$ if $\theta_2 \geq R_i$.

The data obtained is used for the majority, where the classification result with the greatest reputation is selected.

3. Results

The fusion was carried out as described above, it was performed on a dataset collected from eight PD patients used their smartphones on a daily basis over a 30-day period. The data were pre-processed and compared with the expert scores used MDS-UPDRS scale for assessing postural tremor. The classification was performed using 10-fold cross-validation and the Batch Ensemble Decision Tree (BEDT). To determine the quality of the classification models, the ROC Area, F-Measure, and accuracy are used. These metrics for local models are 0.915, 0.851 and 85% respectively. The threshold values for reputation-based voting for the first model is $\theta = 0.2$, and for the second model are $\theta_1 = 10.5$, $\theta_2 = 7.8$ respectively. Reputation was assessed using the first and second models and the corresponding thresholds. We also compare the fusion results with the average of the individual local models. The second column in Table 2 contains average individual error rates obtained for each local model operating alone. The third column shows the average error rates achieved by fusing.

Table 2. Results achieved for local and global models

MDS-UPDRS score	Individual error rate	Global fusion error rate	% error rate reduction
0: Normal	0.179	0.136935	23.5
1: Slight	0.282	0.212346	24.7
2: Mild	0.042	0.030744	26.8
3: Moderate	0.166	0.132966	19.9
4: Severe	0.181	0.140094	22.6

The first and second reputation models are used in the global fusion model to reach consensus. Both reputation-based fusion models showed the classes with the highest reputation values for the right hand equal to mild tremor and the left hand equal to moderate tremor, which is in line with the experts' assessment. The reduction of average error rates achieved by fusing is 23.5%. This suggests that reputation aware technique can contribute, through fusion, for quantifying hand tremor severity form everyday interaction with a smartphone that gives a reason to consider this approach as promising for further research and applications.

4. Conclusion

Accurate classification and differential diagnosis of common tremor syndromes is one of the first steps towards the wide introduction of the remote health monitoring systems, the implementation of high-quality feedback with the physician and, accordingly, the timely detection and treatment of the symptoms of Parkinson's disease. The proposed framework is developed to be in line with the efforts toward predictive healthcare data analytics, in capturing early signs of PD and monitoring Parkinsonian symptoms over time. This approach congregates well-known methods for testing patients with PD, namely specially designed tests built-in as an application in a smartphone and enables to perform analysis of data in a different time and population scales.

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