Towards a Personal At-Home Lab for Motion Video Tracking in Patients with Parkinson's Disease

Alexander Yu. Meigal, Kirill S. Prokhorov, Nikita A. Bazhenov, Liudmila I. Gerasimova-Meigal, Dmitry G. Korzun
Petrozavodsk State University (PetrSU)
Petrozavodsk, Russia
{meigal, gerasimova}@petrsu.ru, k_pro@bk.ru, {bazhenov, dkorzun}@cs.karelia.ru

***Abstract*—Many digital healthcare services now employ the opportunities of mobile and smart Internet technologies. The Internet is used to deliver such services as medical consultations, diagnosis, and prescriptions. The services are constructed and delivered in the ubiquitous style—anywhere, anytime, and using surrounding devices of our everyday life. In this paper, we discuss the opportunities of motion video tracking in at-home settings for a patient. Parkinson's disease (PD) serves as a case study. First, we define the problem of motion video tracking in PD patients. Then, we consider Internet-enabled methods for motion video tracking, which are essentially restricted with professional settings of a medical environment. Finally, we propose to create a personal at-home lab based on such cheap home-based cameras as any smartphone has. Our early experiment shows that such cameras provide reliable capture quality for the practical use in PD patient motion video tracking.**

I. Introduction

The observable progress in mobile and smart Internet technologies enables the cybermedicine approach to development of digital healthcare services, e.g., see [1], [2], [3], [4], [5]. The Internet becomes primarily used to deliver such services as medical consultations, diagnosis, and prescriptions. Mobile services provide end-users (patients) with online and personalized access to consultations and treatment with medical professionals. Furthermore, the emergency of Internet of Things (IoT) technologies makes components of our surroundings (things) smart and connected.

In this paper, we consider the development problem of service-oriented systems for mobile personalized healthcare. Such a system provides digital support for many mobile patients, doctors, and other stakeholders. Many healthcare services eventually become social by taking into account the activity of patients and their collaborative work (in participation with medical professionals and other interested parties), i.e., becoming a kind of socio-cyber-medicine system [5].

A particular class of socially important neurological disorders is Parkinson's disease (PD). According to the Parkinson's Disease Foundation, now more than 10 million people are affected worldwide (see http://www.pdf.org/parkinson_statistics). PD is becoming the second of most common neurodegenerative movement disorders. That results in high economic burden due to both medication costs and lost income from inability to work.

Many digital healthcare services, and PD in particular, now employ the opportunities of mobile and smart Internet technologies. The Internet is used to deliver such services as medical consultations, diagnosis, and prescriptions. The services are constructed and delivered in the ubiquitous style (anywhere, anytime, by appropriate devices). Furthermore, the emergency of IoT technologies makes our surroundings smart, and such smart everyday objects can be involved into the healthcare service construction and delivery. In this paper, we focus on the services for motion video tracking in everyday at-home settings in PD patients.

Recent methods for motion video tracking are essentially restricted with clinical and laboratory setting. They require powerful digital equipment and sophisticated algorithms to make video capture and subsequent data mining. Now a new trend becomes observable when our everyday life equipment is used in healthcare services, and smartphones and other home-based devices with cameras represent a very promising class of this equipment. We propose a concept of a personal at-home lab where the central component is such a home-based camera. The camera becomes smart and able to support its PD patient (in home) and doctor (remote) with motion detection-based services. This service intelligence is primarily achieved due to delegation of complicated recordings collection, big data mining, and knowledge reasoning to such computational components as video server (cloud computing technologies) and semantic information broker (smart spaces technologies).

The rest of the paper is organized as follows. Section II defines the problem of motion video tracking in PD patients. Section III experimentally studies outpatient motion video tracking in PD patients. Section IV proposes our concept of a personal at-home lab based on low-cost cameras that many smartphones have. Finally, Section V concludes the paper.

II. Problem

Parkinson's disease (PD) is in the focus of modern neurosciences due to the following long existing reasons.

1) PD's incidence in developed countries in people older than 60 years is over 1% of population and it is 4% over the age 80 years, and rising [6].
2) PD is a life-limiting disease that notably worsens quality of life of PD by numerous motor and non-motor deficits [7].

PD patients often either retire preterm or change their accustomed profession, since their motor coordination, force, and reaction time is decreased, and professional skills are impaired. As a result, PD exerts the sound economic and

TABLE I. EXAMPLE SMARTPHONE APPLICATIONS FOR PERSONAL AT-HOME SUPPORT

Application	Description	Available at Google Play
CamFind	Image recognition of items and mobile visual search.	https://play.google.com/store/apps/details?id=com.msearcher.camfind
Image search	Image searching application supported with Google searching engine.	https://play.google.com/store/apps/details?id=kr.kkh.image_search2
Color Grab	On-the-go application to capture and recognize colors by pointing the camera.	https://play.google.com/store/apps/details?id=com.loomatix.colorgrab
Gait 101	Learning application to train by analyzing and understanding human movement.	https://play.google.com/store/apps/details?id=com.physiou.gait
Parkinson's Toolkit	Authoritative clinical practice guide for treating Parkinson's disease.	https://play.google.com/store/apps/details?id=com.apps.parkinsons
Parkinson's EasyCall	Phone call application for people having dexterity issues.	https://play.google.com/store/apps/details?id=co.uk.org.parkinsons
Parkinson's Central	Application to empower PD people who care to take control of the disease.	https://play.google.com/store/apps/details?id=com.parktool.aaa

humanitarian impact on the society. In particular, it can exceed 15000 USD per patient [8]. PD patients have many unmet needs in psychosocial domain [9]. Therefore, sophistication of palliative care would have considerably reduced suffering in daily life and activities [10], [11].

PD cannot be regarded as the one that may have provoked direct and fast lethal outcome. Nevertheless, the mortality in PD patients is increased [11]. Such complications as spontaneous falls driven by postural instability during turning may result in head injuries or cervical hip fracture. In tight places, PD patients move awkward and often collide with furniture, again with risk to fall. Post-traumatic long term bed care regime may, in some instances, lead to a lethal lung infection. Additionally, depression, anxiety, apathy, autonomic, sleep, sensory, and cognition disorders appear as strongly disabling PD factors [12], [13]. At worst, PD patients found themselves bound to wheel-chair. In many important senses, PD mirrors advanced cancer, since such symptoms as pain, motor disability and fatigue, grief, identity and spiritual well-being are common for these pathologies [14].

The current therapy of PD is mostly symptomatic and based on dopamine replenishment in the brain. That treatment proved highly efficient. Still, either habituation to pharmacotherapy with imperative to increase dosage of a medicine or unwanted side effects in the form of dyskinesia/freezing/psychotic attacks often takes place [15]. Such medical situation is aggravated by the concurrent age-related problems, since PD is a disease of the elder people (aged over 50 years). The growing PD incidence and increasing portion of aged people in developed countries, the long chronic course of PD, the older age of PD patients, and relatively effective anti-PD therapy altogether generate a situation when elder patients either stay alone in big apartments without care or supervision, or lead a totally lone life. As such, elder people and PD patients share many problems of their daily activities. Potentially, all the above accidents and complications of PD may well have taken place also for the elderly with the same negative outcome. To cope with that, an information system can be created to support PD patients to raise awareness of their current condition and even to involve them to shared decision making with neurologist about their care [16]. As a result, moving from a physician-centered toward patient-centered care has been emerging [17]. In ideal, at home detection and analysis is needed to help a PD patient to control her/his risk, e.g., to freezing of gait [18].

Monitoring of various physiological parameters in PD patients is acknowledged as a reliable and promising researching approach. It allows more profoundly analyzing physiological functions, either motor or non-motor. As a result, right diagnosis is supported. Monitoring provides both online and offline analysis, storing of data, and big data mining. Recent techniques and systems for PD monitoring are presented, e.g., in [19], [20], [21]. For the use of monitoring, the motor disorders in PD patients appear as the most conspicuous ones. The so-called motor triad of PD that includes rest tremor, muscle rigidity (enhanced muscle tone), and bradyakinesia (slowed movements or inability to start moving) strongly reduces muscular performance to simple and monotonous motor activity. Postural instability and pronounced fatigability bring additional motor deficit. Spontaneous falls, freezing of gait, and psychotic attacks must be regarded as primary targets for a mobile detection and analysis system that operates continuously at home environment.

In clinical and laboratory settings, motion video capture (MVC) technique is increasingly used to reveal specific features of PD. Most of proposals are based on tracking the motor or cognitive impairment during varied tests in, e.g., performing the timed up and go test TUG, sitting-rising test or various gait tests. In contrast, a system for the daily assessment of walking ability using a distance sensor array device was proposed in [22]. The system uses a simple device comprising inexpensive distance sensors to provide preservation of privacy, ease of installation, and low cost.

In recent years, modern smartphone-based architectures provide a low cost alternative to clinical and laboratory environments to detect symptoms of various socially important diseases [23], [24], [25]. In particular, accelerometry measurements from the mobile user can be used for freezing of gait events [26] and for assessing gait or finger movements in PD patients [27]. Collecting and data mining for smartphone accelerometer recordings is considered [28] to find some kinematic features in the analysis of tremor and PD. Various mobile systems for monitoring, assessment, and management of PD patients were proposed [29], [20], [30]. Many mobile applications for mobile and personal information support can be found at Google Play, see some examples in Table I.

As a particular application domain, smartphones now are becoming utilized in solving various tasks of motion video detection. For instance, the Microsoft Kinect sensor (Kinect) provides a low-cost solution for clinical and home-based assessment of movement symptoms in people with PD [31]. Kinect can be used as everyday alternative of complex multi-camera systems for detection and analysis of gait features during the treatment of neurological disorders [32]. Some mobile applications for motion detection can be found at Google Play, see examples in Table II as well as their popularity (measured in user votes).

We assume that a smartphone in home settings would have allowed tracking motion of a PD patient in a more "natural" environment, i.e., in everyday life surrounding [29], [33], [22], [21]. Instant motion analysis intelligently provides decisions for behavior and care advises. To the best of our knowledge, the potential of smarthphones have not yet been essentially

TABLE II. EXAMPLE SMARTPHONE APPLICATIONS FOR MOBILE MOTION DETECTION

Application	Description	Available at Google Play	Votes
Salienteye	Home security system with use of the camera.	https://play.google.com/store/apps/details?id=com.mantishrimp.salienteye	17471
Motion Detector Pro	Application that uses built-in camera to detect movements in the surrounding area.	https://play.google.com/store/apps/details?id=dk.mvainformatics.android.motiondetectorpro.activity	11441
Motion Detector Video Recorder	HD video recorder that triggers on motion detection.	https://play.google.com/store/apps/details?id=com.zenaapps.motiondetectorvideorecorder	699
Motion Detector	Application that detects motion automatically by smart use of smartphone camera.	https://play.google.com/store/apps/details?id=com.mtat.motiondetector	545
Realvisor	Video surveillance via smartphone camera.	https://play.google.com/store/apps/details?id=com.reallyvision.realvisor3	138

realized for motion video detection. In this way, we propose to hybridize opportunities of currently available motion video capture with the opportunities that a smartphone can provide. Furthermore, PD appears as a kind of perfect and insidious pathology that interferes with almost all spheres of the human organism functioning and daily activities. In that sense, PD is as an ideal candidate to exploit smartphones as a basis for such a home video motion tracking lab.

To test that assumption, we explored the feasibility of merging the functionality of a customary available motion video capture complex Videoanaliz Biosoft 3D (Biosoft Ltd., Moscow, Russia) with smartphones Xiaomi Mi on the Android platform. Additionally, we explored whether a regular surveillance video camera has potential to serve for video capture. The ultimate outcome of that would be a kind of personal at-home lab for the use of a PD patient, her/his family, and local doctors. The lab supports the needs of instant online diagnostics, tracking, and advising. The above can be summarized in the brief and laconic formula:

$$\text{Personal At-Home Lab} = \\ = \text{Motion Video Capture} + \text{SmartPhone}.$$

III. REFERENCE SOLUTIONS TO MOTION VIDEO TRACKING

We study solutions to motion video tracking by putting together experimental conditions of 1) video acquiring equipment (motion video capture, surveillance video camera and smartphone) with 2) illumination (day light, artificial illumination, near darkness condition and IR light + artificial light, flash). Our experiments are controlled; they carried out in laboratory conditions aiming to simulate natural settings [34].

A. Hardware and software

As we discussed in Section II, the motion video capture technique is commonly used to study motor function in humans. This technique allows assessing joint angles, position, velocity, and acceleration of a limb in 3D. In our experimental study, we used the Videoanaliz Biosoft 3D complex (Biosoft Ltd., Moscow, Russia) due its easy commercial availability and active use in Russia for research purposes [35].

The concept of motion video capture system is shown in Fig. 1. Our testbed uses the following hardware and software.

1) PC (Fireware-1394b) with preset OS Windows XP.
2) Multifunctional motherboard NI PCI-6071E (National Instruments, Texas, USA), with driver NI PCI-6071E6071E (National Instruments, Texas, USA).
3) Two video cameras Baumer TXG (90 Hz) equipped by interface cable Fireware-1394b and a cable for synchronization of video camera and board.

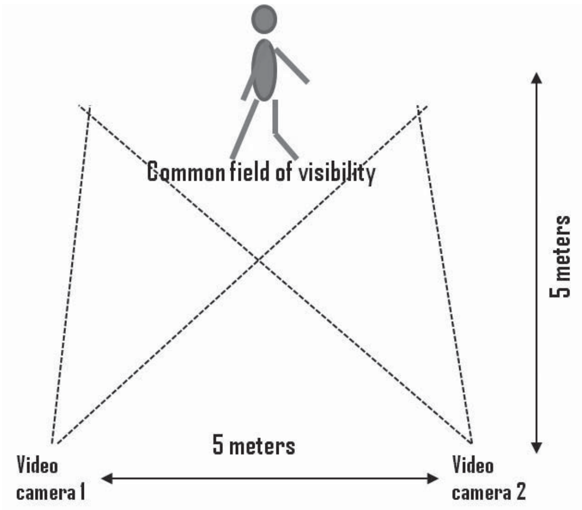

Fig. 1. Disposition of cameras and subject in motion video tracking

4) IR backlight.
5) Test object and a set of self adhesive spherical light returning elements.
6) Video information was stored in AVI format without archiving at 25-180 Hz.

The software performs automated identification of labels on video, computation of their coordinates in 3D, construction of a 3D model of a subject and kinetogram (with the option to superimpose it with original video). The data can also be recorded in the TXT and MS Excel formats for further analysis. Illustration is provided in Fig. 2, where the Y coordinate is for horizontal movement and the Z coordinate is for vertical movement. Numerated labels (open circles) represent position of light-returning elements on skin or wearable over: (1) head, (2) shoulder, (3) elbow joint, (4) wrist, (5) hip, (6) knee, (7) ankle, and (8) toes.

B. Clinical outcome measure

To assess mobility in PD patients they were asked to go through the TUG (timed up-and-go) test. This test is acknowledged as one of the most informative in neurology [36]. To perform the TUG test, subjects were instructed to rise from a chair, then walk three meters forth, turn around, walk back to the chair, and finally sit down. Usually, to complete the TUG test it takes between 6 to 12 s. Very often, the TUG is performed in association with the dual task (mental task) to evaluate cognitive functionality of subjects.

After the light-returning elements are unilaterally placed on the right side, subjects dressed in pants, foot bare, performed

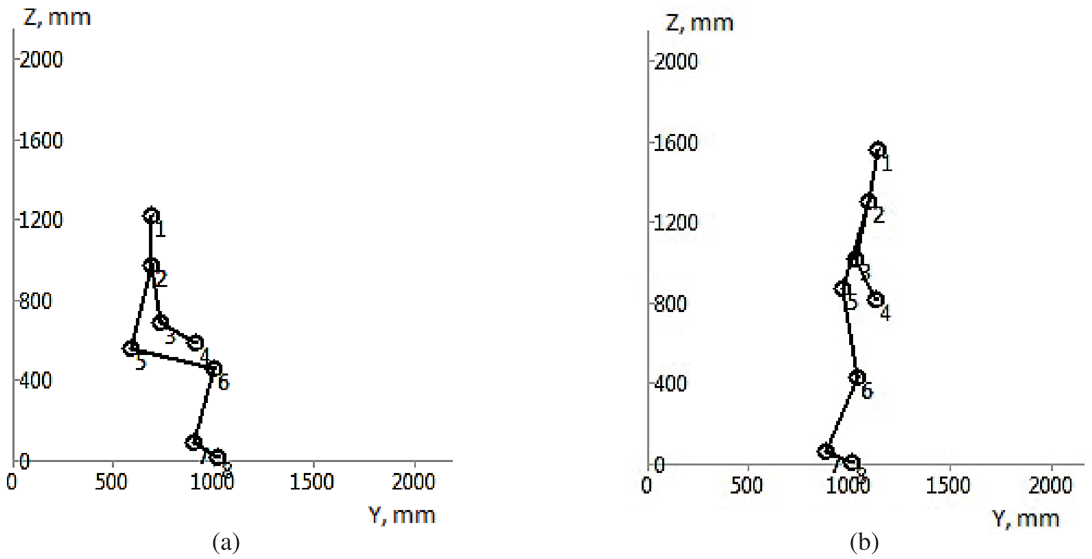

Fig. 2. One-plane model of a subject: (a) in sitting position and (b) in standing position.

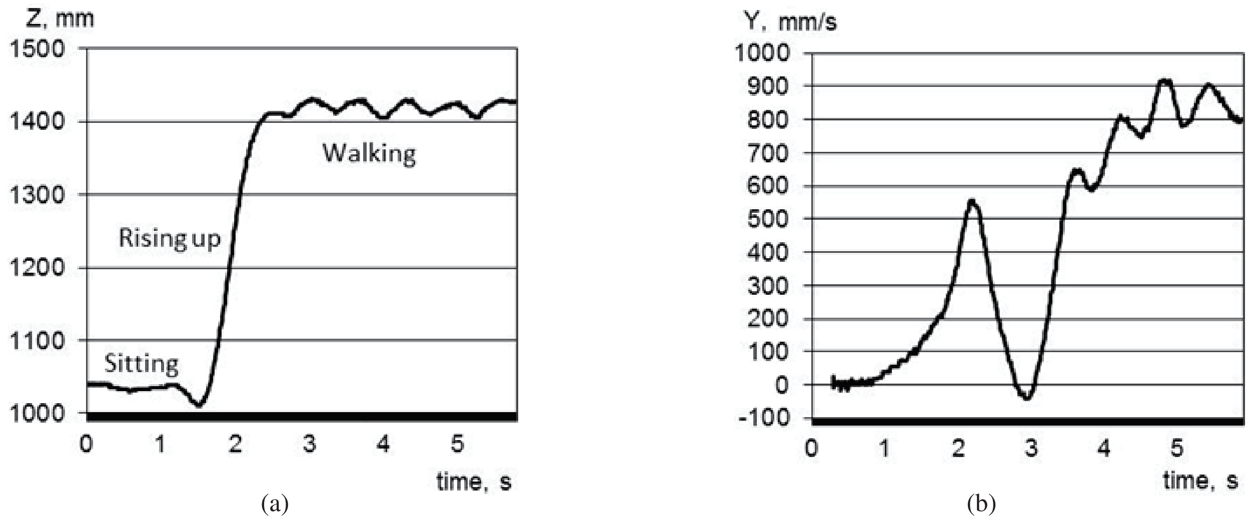

Fig. 3. Head movement (label 1 from Fig. 2) in the Z and Y coordinates during sitting, rising up, and walking: (a) trajectory and (b) velocity.

TABLE III. IDENTIFICATION OF QUALITY WHEN COMPARING CAMERAS WITH GOOD AND BAD LIGHTING

Settings	Bad lighting	Good lighting
Laboratory	High image quality [With the support of infrared light]	Very high image quality
Smartphone	High image quality [With the support of a flashlight]	High image quality
Surveillance	Average image quality [With the support of built-in light sensor]	Average image quality

the TUG. For the purpose of video analysis we utilized only the first two steps of the TUG test — rising from chair (sit-to-stand phase) and walking forth (usually 4-5 strides). An example of trajectory of coordinate of a single label (head, label 1) during the TUG test is presented in Fig. 3.

One can observe in Fig. 3 (a) that prior to rising up from the chair subject has to tilt forth to place her/his center of gravity over the feet. That makes the head moving down. Then the head rises up along with the whole body, and finally a clear sine wave trajectory depicts evolutions of head position during stepping. These up and down evolutions originate from recursions of the center of gravity during steps. Corresponding behavior of velocity values for the head is shown in Fig. 3 (b).

Experiments were conducted on the three different classes of video capture devices, as summarized in Table III.

1) Laboratory cameras: professional cameras with pre-installed specialized software.
2) Smartphone: an embedded camera of mobile phone.
3) Surveillance camera: a rotary IP-camera at home.

Examples screenshots of light-returning objects are shown in Fig. 4. They are obtained with help of surveillance camera and smartphone. We can see that the smartphone camera has almost the same quality as the surveillance cameras. The only disadvantage is that smartphone does not have high frame rate (actually, we do not need it). Surveillance camera has acceptable quality although the used camera was quite old in

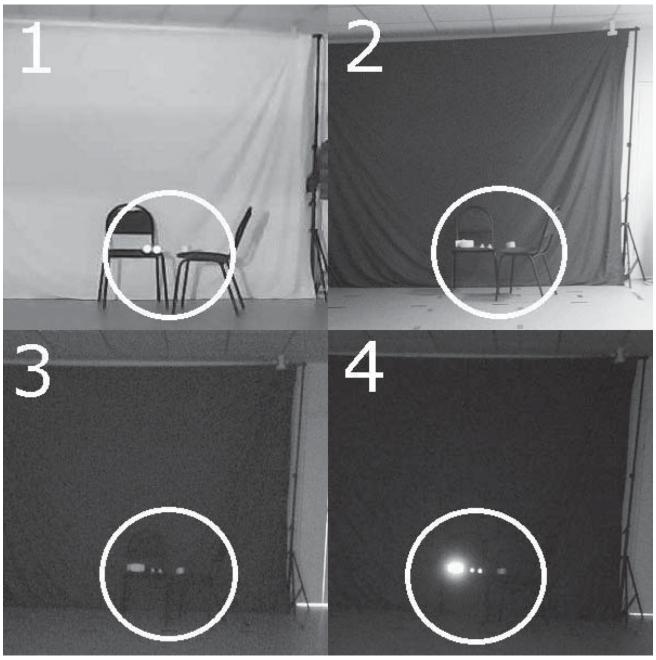

Fig. 4. Screenshots of two light-returning spherical elements and band roll obtained with help of surveillance camera in IR ("night vision") regime (1) under regular artificial illumination, (2) by smartphone under artificial illumination along with daylight, (3) in darkness (twilight), and (4) with flash illumination in darkness.

the experiment. We expect that modern cameras would have had almost the same quality as on smartphone cameras. The clear advantage of this camera is its light sensor.

IV. Concept of personal at-home lab

We develop a mobile home-based system to capture motion using smarthones and other everyday equipment with further application to examine the motor function in PD patients. As we discussed previously in Section II, PD is caused by neurons degeneration of the black substance in brain, resulted in lowered production of the neurotransmitter dopamine. This result is known to play crucial role both in cognitive and motor activity. To start with that, we posed a question whether PD motor symptoms could be seen using a typical camera on smartphone or on regular surveillance camera.

We consider existing solutions for using smartphones in PD people monitoring, assessment, and management. In particular, we utilize a novel remote approach to enrollment, in which participants self-guide through visually engaging yet complete informed consent process prior to deciding to join the study. A critical aspect of this transparent consent process is providing the participants with an explicit decision point specifying if the data they donate to the study can also be used for secondary research purposes.

We designated the following PD symptoms in the assumption that they are the most evident and cardinal from the point of view of home-based healthcare.

- Muscular rigidity.
- Brady- and akinesia.
- Rest tremor.
- Postural instability.

These PD symptoms define the services that the system provides to its users (patient in home and remote doctor). To construct these services, the patient (examinee) needs to perform some tests. She/he does it within appropriate periods of time (minutes or seconds). The home-based camera (e.g., on smartphone) captures video for these tests. The following scenario is proposed for the system to construct the services.

1) The patient is instructed to pass through the motor tests occasionally, self-managed, and unsupervised. In particular, the patient can perform some certain exercises.
2) Recordings on patient's gait are collected from one or more home cameras. In particular, a smartphone camera can be used.
3) The collected data are analyzed locally and/or transmitted to remote destination using the Internet for further processing and use.

Our concept model to implement this scenario is depicted in Fig. 5. The model follows the M3 architecture [37], [38], [39] for smart spaces. The key property is support of service intelligence [23] in this healthcare scenario for motion video detection. As the result, a smart space is deployed around the patient using surrounding devices and Internet access.

The video recording are collected at the dedicated video server. The server achieves the video data from the home-based camera. Offline and online modes are supported. Semantic Information Broker (SIB) relates the information fragments (e.g., keeping links to appropriate video recordings, their description, and interpretations). In general, a semantic network is created and maintained to represent the knowledge mined from the video data. SIB is requested from the doctor or user sides to receive services for motion detection of the PD symptoms. The doctor can leave comments for the analyzed data and make conclusions about the patient's condition. The patient can receive this information in the form of services. As a result, the cameras become connected with data analyzers (servers) and users (patients, doctors).

This concept model makes a camera "smart". Furthermore, the provided services also become "smart". In particular, the intelligence appears in the following properties.

- Recognition of observable objects in the lens.
- Analysis of video data flows and captured images from the camera in order to make the motion detection.

Results of this analysis leads to construction of such smart services as:

- warnings about patient condition,
- sending notices to relatives and the doctor,
- calling an ambulance.

Table IV summarizes possible deployment options for the entities introduced in the concept model. The table shows the service intelligence level in dependence on architectural combination of involved participants (smartphone, SIB, video

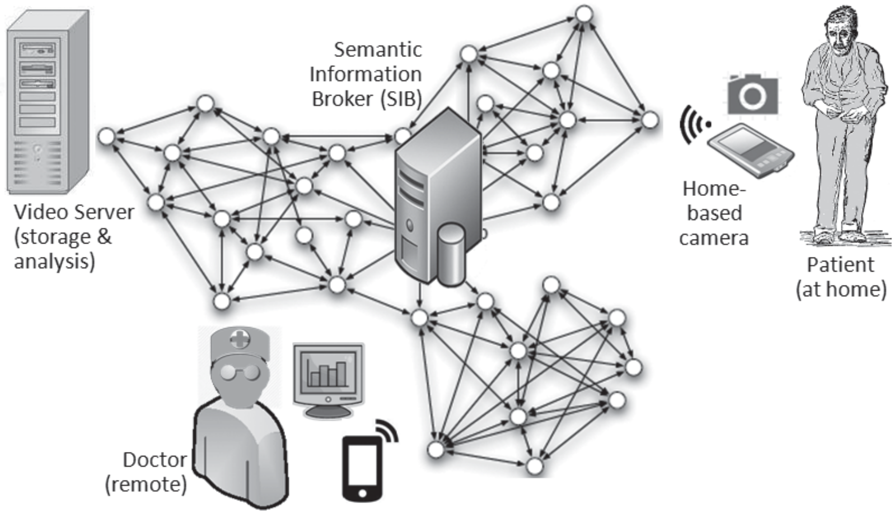

Fig. 5. M3-based concept of personal at-home system of services for motion video detection

TABLE IV. DEPLOYMENT OPTIONS

Architectural combination	Motion detection-based services	Service intelligence level	Development and deployment complexity
Smartphone	Simple services such as video streaming or recognition of simple objects, silhouettes, and movements.	Smartphone becomes a meta-device acting as 1) video data sensor, 2) data mining center, and 3) access and delivery point to services.	Strong requirements in computing resources to perform the complicated tasks set on one mobile device.
Smartphone + Server	Advanced services for recognition and analysis of PD symptoms in large video flows.	Services are constructed in a traditional way using the server (with possibly cloud infrastructure) and known algorithms for pattern recognition in video data.	Efficient delegation of computations from mobile devices to the server can be non-easy and subject to resource restrictions of mobile network communication.
Smartphone + SIB	Semantic services for PD symptom recognition are constructed in context-aware manner and locally in home environment.	Inferring context and other "personalized" knowledge from established semantic relations to adapt the services to the user, current situation, and needs.	High load onto SIB since it has to perform complex motion detection algorithms and semantically relate the results in service construction.
Smartphone + Server + SIB	Advanced service composition is possible when multiple PD symptoms are taken into account.	Basic services uses known algorithms for pattern recognition in video data while the results are composed to reflect the semantics of the observed data.	Complicated distributed system with data-intensive processing, big data mining, and distributed knowledge reasoning.

server). Higher intelligence level increases the development and deployment complexity. The simplest option involves only one smartphone, although construction of smart services needs the use of powerful smartphones in this case.

V. Conclusion

This paper reviewed recent trends in mobile and smart Internet technologies for development of motion video tracking services in everyday at-home settings. We study the problem of motion video tracking for the particular important class of neurological disorders—Parkinson's disease. We consider emerging methods for motion video tracking, which are essentially restricted with clinical and laboratory setting of professional medicine. We propose a concept for a personal at-home lab, which can be created to support PD patients in their everyday life. The central component of the concept is a home-based camera, which is made smart, similarly as it happens in IoT with things. Our early experiments show that such home-based cameras provide reasonable capture quality for the practical use in PD patients motion video tracking.

Acknowledgment

The reported study was financially supported from Russian Fund for Basic Research according to research project # 16-07-01289. The work of A. Meigal is supported by the Ministry of Education and Science of Russia within project # 17.7302.2017/6.7 of the state research assignment for 2017–2019. The work of D. Korzun is supported by the Ministry of Education and Science of Russia within project # 2.5124.2017/8.9 of the basic part of state research assignment for 2017–2019. The research is implemented within the Government Program of Flagship University Development for Petrozavodsk State University in 2017–2021.

References

[1] S. M. R. Islam, D. Kwak, M. H. Kabir, M. Hossain, and K. S. Kwak, "The internet of things for health care: A comprehensive survey," *IEEE Access*, vol. 3, pp. 678–708, 2015.

[2] E. Balandina, S. Balandin, Y. Koucheryavy, and D. Mouromtsev, "IoT use cases in healthcare and tourism," in *Proc. IEEE 17th Conf. on Business Informatics (CBI 2015)*, vol. 2, Jul. 2015, pp. 37–44.

[3] J. Bravo, D. J. Cook, and G. Riva, "Ambient intelligence for health environments," *Journal of Biomedical Informatics*, vol. 64, pp. 207–210, 2016.

[4] D. G. Korzun, "Internet of things meets mobile health systems in smart spaces: An overview," in *Internet of Things and Big Data Technologies for Next Generation Healthcare*, ser. Studies in Big Data, C. Bhatt, N. Dey, and A. S. Ashour, Eds. Springer International Publishing, 2017, vol. 23, pp. 111–129.

[5] Y. V. Zavyalova, D. G. Korzun, A. Y. Meigal, and A. V. Borodin, "Towards the development of smart spaces-based socio-cyber-medicine systems," *International Journal of Embedded and Real-Time Communication Systems (IJERTCS). Special Issue on Big Data Analytics and*

Intelligent Environments in Internet of Things, vol. 8, no. 1, pp. 45–63, 2017.

[6] L. M. de Lau and M. M. Breteler, "Epidemiology of Parkinson's disease," *The Lancet Neurology*, vol. 5, no. 6, pp. 525–535, 2006.

[7] C. H. Dowding, C. L. Shenton, and S. S. Salek, "A review of the health-related quality of life and economic impact of Parkinson's disease," *Drugs & Aging*, vol. 23, no. 9, pp. 693–721, Sep 2006.

[8] K. Noyes, H. Liu, Y. Li, R. Holloway, and A. W. Dick, "Economic burden associated with Parkinson's disease on elderly medicare beneficiaries," *Movement Disorders*, vol. 21, no. 3, pp. 362–372, 2006.

[9] A. D. Ventura, S. Burney, J. Brooker, J. Fletcher, and L. Ricciardelli, "Home-based palliative care: A systematic literature review of the self-reported unmet needs of patients and carers," *Palliative Medicine*, vol. 28, no. 5, pp. 391–402, 2014.

[10] E. W. Richfield, E. J. Jones, and J. E. Alty, "Palliative care for Parkinson's disease: A summary of the evidence and future directions," *Palliative Medicine*, vol. 27, no. 9, pp. 805–810, 2013.

[11] J. M. Miyasaki and B. Kluger, "Palliative care for Parkinson's disease: Has the time come?" *Current Neurology and Neuroscience Reports*, vol. 15, pp. 1–7, Mar. 2015.

[12] B. A. Racette and A. W. Willis, "Time to change the blind men and the elephant approach to Parkinson disease?" *Neurology*, vol. 85, no. 2, pp. 190–196, 2015.

[13] I. Boersma, J. Jones, J. Carter, D. Bekelman, J. Miyasaki, J. Kutner, and B. Kluger, "Parkinson disease patients' perspectives on palliative care needs," *Neurology: Clinical Practice*, vol. 6, no. 3, pp. 209–219, 2016.

[14] R. Ghoche, "The conceptual framework of palliative care applied to advanced Parkinson's disease," *Parkinsonism & Related Disorders*, vol. 18, pp. S2–S5, Dec. 2012.

[15] W. Oertel and J. B. Schulz, "Current and experimental treatments of Parkinson disease: A guide for neuroscientists," *Journal of Neurochemistry*, vol. 139, pp. 325–337, 2016.

[16] S. Kreimer, "Shared decision-making: How to involve patients in their own neurological care," *Neurology Today*, vol. 13, no. 14, pp. 20–23, Jul. 2013.

[17] M. Benham-Hutchins, N. Staggers, M. Mackert, A. H. Johnson, and D. deBronkart, ""I want to know everything": a qualitative study of perspectives from patients with chronic diseases on sharing health information during hospitalization," *BMC Health Services Research*, vol. 17, no. 1, pp. 1–10, Aug. 2017.

[18] D. Rodriguez-Martin, A. Sama, C. Perez-Lopez, A. Catala, J. M. M. Arostegui, J. Cabestany, A. Bayes, S. Alcaine, B. Mestre, A. Prats, M. C. Crespo, T. J. Counihana, P. Browne, L. R. Quinlan, G. OLaighin, D. Sweeney, H. Lewy, J. Azuri, G. Vainstein, R. Annicchiarico, A. Costa, and A. Rodriguez-Molinero, "Home detection of freezing of gait using support vector machines through a single waist-worn triaxial accelerometer," *PLoS ONE*, vol. 12, no. 2, 2017.

[19] S. Herrlich, S. Spieth, R. Nouna, R. Zengerle, L. I. Giannola, D. E. Pardo-Ayala, E. Federico, and P. Garino, *Ambulatory Treatment and Telemonitoring of Patients with Parkinson's Disease*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2011, pp. 295–305.

[20] A. T. Tzallas, M. G. Tsipouras, G. Rigas, D. G. Tsalikakis, E. C. Karvounis, M. Chondrogiorgi, F. Psomadellis, J. Cancela, M. Pastorino, M. T. A. Waldmeyer, S. Konitsiotis, and D. I. Fotiadis, "PERFORM: A system for monitoring, assessment and management of patients with Parkinson's disease," *Sensors*, vol. 14, no. 11, pp. 21 329–21 357, 2014.

[21] D. Pan, R. Dhall, A. Lieberman, and D. B. Petitti, "A mobile cloud-based Parkinson's disease assessment system for home-based monitoring," *JMIR mHealth and uHealth*, vol. 3, pp. 1–15, 2015.

[22] R. Fukui, H. Ifuku, M. Watanabe, M. Shimosaka, and T. Sato, "Easy-to-install system for daily walking ability assessment using a distance sensor array," *Journal of Ambient Intelligence and Smart Environments*, vol. 7, no. 3, pp. 375–387, 2015.

[23] D. Korzun, I. Nikolaevskiy, and A. Gurtov, "Service intelligence support for medical sensor networks in personalized mobile health systems," in *Internet of Things, Smart Spaces, and Next Generation Networks and Systems. Proc. 15th Int'l Conf. Next Generation Wired/Wireless Networking and 8th Conf. on Internet of Things and Smart Spaces (NEW2AN/ruSMART 2015), LNCS 9247*, S. Balandin, S. Andreev, and Y. Koucheryavy, Eds. Springer, Aug. 2015, pp. 116–127.

[24] E. R. Dorsey, Y.-F. Yvonne Chan, M. V. McConnell, S. Y. Shaw, A. D. Trister, and S. H. Friend, "The use of smartphones for health research," *Academic Medicine*, vol. 92, no. 2, pp. 157–160, 2017.

[25] N. E. Chaibub, B. Bot, T. Perumal, L. Omberg, J. Guinney, M. Kellen, A. Klein, S. H. Friend, and A. D. Trister, "Personalized hypothesis tests for detecting medication response in parkinson disease patients using iphone sensor data," in *Pacific Symposium on Biocomputing*, 2016, pp. 273–284.

[26] M. Capecci, L. Pepa, F. Verdini, and M. G. Ceravolo, "A smartphone-based architecture to detect and quantify freezing of gait in Parkinson's disease," *Gait & Posture*, vol. 50, no. Supplement C, pp. 28–33, 2016.

[27] S. Arora, V. Venkataraman, A. Zhan, S. Donohue, K. Biglan, E. Dorsey, and M. Little, "Detecting and monitoring the symptoms of Parkinson's disease using smartphones: A pilot study," *Parkinsonism & Related Disorders*, vol. 21, no. 6, pp. 650–653, 2015.

[28] S. Barrantes, A. J. S. Egea, H. A. G. Rojas, M. J. Marti, Y. Compta, F. Valldeoriola, E. S. Mezquita, E. Tolosa, and J. Valls-Sole, "Differential diagnosis between Parkinson's disease and essential tremor using the smartphone's accelerometer," *PLoS ONE*, vol. 12, pp. 1–12, Aug. 2017.

[29] S. Patel, H. Park, P. Bonato, L. Chan, and M. Rodgers, "A review of wearable sensors and systems with application in rehabilitation," *Journal of NeuroEngineering and Rehabilitation*, vol. 9, no. 1, pp. 1–17, Apr. 2012.

[30] V. Sharma, K. Mankodiya, F. De La Torre, A. Zhang, N. Ryan, T. G. N. Ton, R. Gandhi, and S. Jain, *SPARK: Personalized Parkinson Disease Interventions through Synergy between a Smartphone and a Smartwatch*. Cham: Springer International Publishing, 2014, pp. 103–114.

[31] B. Galna, G. Barry, D. Jackson, D. Mhiripiri, P. Olivier, and L. Rochester, "Accuracy of the Microsoft Kinect sensor for measuring movement in people with Parkinson's disease," *Gait & Posture*, vol. 39, no. 4, pp. 1062–1068, 2014.

[32] O. Ťupa, A. Procházka, O. Vyšata, M. Schätz, J. Mareš, M. Vališ, and V. Mařík, "Motion tracking and gait feature estimation for recognising Parkinson's disease using MS Kinect," *BioMedical Engineering OnLine*, vol. 14, no. 1, pp. 1–20, Oct. 2015.

[33] C. L. Pulliam, S. R. Eichenseer, C. G. Goetz, O. Waln, C. B. Hunter, J. Jankovic, D. Vaillancourt, J. Giuffrida, and D. A. Heldman, "Continuous in-home monitoring of essential tremor," *Parkinsonism & Related Disorders*, vol. 20, pp. 37–40, 2014.

[34] J. L. Reyes-Ortiz, A. Ghio, X. Parra-Llanas, D. Anguita, J. Cabestany, and A. Català, "Human activity and motion disorder recognition: Towards smarter interactive cognitive environments," in *Proc. 21th European Symp. on Artificial Neural Networks, Computational Intelligence and Machine Learning (ESANN 2013)*, Apr. 2013, pp. 403–412.

[35] A. V. Shpakov, A. V. Voronov, E. V. Fomina, N. I. Lysova, M. Chernova, and I. B. Kozlovskaia, "Comparative efficiency of different regimens of locomotor training in prolonged space flights as estimated from the data on biomechanical and electromyographic parameters of walking," *Human Physiology*, vol. 39, no. 2, pp. 162–170, Mar. 2013.

[36] M. Son, C. Youm, S. Cheon, J. Kim, M. Lee, Y. Kim, J. Kim, and H. Sung, "Evaluation of the turning characteristics according to the severity of parkinson disease during the timed up and go test," *Aging Clinical and Experimental Research*, Feb. 2017.

[37] S. Balandin and H. Waris, "Key properties in the development of smart spaces," in *Proc. 5th Int'l Conf. Universal Access in Human-Computer Interaction (UAHCI '09). Part II: Intelligent and Ubiquitous Interaction Environments, LNCS 5615*, C. Stephanidis, Ed. Springer-Verlag, Jul. 2009, pp. 3–12.

[38] J. Honkola, H. Laine, R. Brown, and O. Tyrkkö, "Smart-M3 information sharing platform," in *Proc. IEEE Symp. Computers and Communications (ISCC'10)*. IEEE Computer Society, Jun. 2010, pp. 1041–1046.

[39] D. G. Korzun, S. I. Balandin, A. M. Kashevnik, A. V. Smirnov, and A. V. Gurtov, "Smart spaces-based application development: M3 architecture, design principles, use cases, and evaluation," *International Journal of Embedded and Real-Time Communication Systems (IJERTCS)*, vol. 8, no. 2, pp. 66–100, 2017.