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Frequency based assessment of surgical activities

Abstract: In hospitals the duration of surgeries plays a decisive role in many areas, such as patient safety or financial aspects. By utilizing accurate automated online prediction efficient surgical patient care and effective resource management can be attained. In this work several surgical activities during an intervention were examined for their potential to forecast the remaining intervention time. The method used was based on analysing in the frequency domain of time series which represented the status of surgical activities during an intervention. A nonparametric estimation of power spectral density was calculated for single surgical tasks during an intervention. The power spectral densities (PSD) of different surgical activities were compared in a leave-one-out cross validation of forty surgical workflow recordings of lumbar discectomies. The results showed that the activity *irrigate* with a mean prediction error of 26 min 23 s is best-suited for determining the remainder of the intervention. To construct a scheduling support for a wider range of surgery types the actions conducted by the surgeon's *right* and *left hand* would eminently be more suitable; the error of the action right hand was 41 min 39 s, yet. In conclusion sophistication into the presented frequency based method might support time and resource management in a general manner.

Keywords: spectral estimation; spectral analysis; surgery; surgical workflow; time series analysis

DOI: 10.1515/CDBME-2015-0038

1 Motivation

Effective resource management is an important method for enhancing the handling of financial and critical safety aspects in modern hospitals. Especially in the operating room (OR) of the future potentials have to exploited to reduce costs of intensive and the risks of hazardous events [1–3]. Such events emerge for several reasons in the OR, like long idle times between sequenced surgical procedures or cancelled interventions due to poor coordination of staff and devices [4, 5].

A straightforward automated time and resource management system could be used to excellent effect to overcome these conflicts. Several approaches towards the real time prediction of phase and intervention time based on a wide range of surgical activities available online are described in literature [6, 7]. In this work we compared single activities of the surgeon to each other in terms of their suitability for predicting the remaining intervention time. The goal of this work is to clarify how a frequency based analogy can predict remaining intervention time. A novel approach for comparison of low level surgical activities is described here. An advantage of this method is that it works with just one single recordable surgical activity. The method was based on frequency domain analysis of time series for surgical procedures, which are usually complex and hard to predict. The periodogram as a nonparametric spectral estimation method was applied to evaluate the eligibility for time prediction of the surgical activities based on forecast the intervention time.

1.1 Related work

Several approaches addressed the real time prediction of phase and intervention time [6, 7]. In many other works methods are described to support OR management based on information available preoperatively, such as the type of intervention [8, 9]. These methods used Hidden Markov Models or Bayesian analysis to describe surgical procedures. Furthermore, classification and comparison of populations (patients, surgeons or systems) was described in [10] and [11] based on measures of statistical comparison like average and standard deviation. The disadvantage of these methods is that the bulk of data, like surgical activities or intraoperative anaesthesia, are necessary to forecast the intervention time. In this work we determined the single most suitable surgical activity to predict intervention time in real time. Obviously accurate real time recognition of surgical activities is required. Surgical activities can be recognized by medical and video data from endoscopes, anaesthesia systems or other signals which are already used in surgical activity recognition systems [6, 12]. These methods are limited to a single surgery type and cannot be transferred directly to each surgery type though. Furthermore, the recent developments in the domain of the integrated and networked OR provided new sources for readily available data concerning surgical activities [13]. In

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conclusion specific signals transmitted inside an OR can be used for automatic real time recording of activities of instruments like a coagulator or a mill.

The purpose of this work is to evaluate which of the activities conducted by a surgeon is most suitable to predict intervention time. Based on spectral estimation and feature extraction sequences surgical activities are compared to one another.

2 Material and methods

In this section we describe four important steps to compare surgical activities in terms of their suitability for intervention time prediction based on spectral estimation.

2.1 Transformation of surgical activities in time series

First off, a cornerstone to compare surgical activities of a specific surgery type is to have recordings of these activities. In our work we relied on recordings in the form of individual Surgical Process Models (iSPM). The iSPM consists of formalized atomic process steps of a surgery; whereby five different perspectives are considered: functional (describes the action), operational (describes the used instruments or devices), spatial (describes the treated body part of the patient), behavioural (describes temporal information) and organizational (describes the executing person) [14]. We concatenated the attributes of the first three perspectives to build an identifier and represented the identified activities' status over the fourth perspective (recorded intervention time). This was done in the form of binary activity sequences over time x(t); x(t) had level 1 while the activity was being conducted and 0 otherwise. By doing so we generated 35 activity time series for one specific surgery type. For this work we focused on lumbar discectomies. Due to several dependencies inside our identifier, like for instance the action *coagulate* and the instrument *coagulator* usually being used in the same activity, we obtained 31 independent activity time series.

2.2 Estimation of the PSD

The second key part is the ascertainment of the similarity between several activities. In order to do this we estimated the PSD for every binary sequence. Based on the straightforward method of power spectrum estimation the so-called periodogram of the discrete activity sequences x[n] is estimated. The periodogram is a classical method and was developed by Schuster [15]. Based on the first derivation of the Fourier Transformation of the activity sequence x[n] the periodogram can be yielded. Thus, the normal form of the spectrum X(Ω) is given by

$$P'_{xx}(\Omega) = \frac{1}{N}|X(\Omega)|^2 \quad [16]$$

The estimation of the periodogram was done with Matlab2014b. The periodogram is often applied in practice for the purpose of spectral estimation; furthermore, it can be calculated in an uncomplicated manner. The size of segments was calculated by choosing the smallest known time interval of any considered activity time series. The smallest time interval helped in fulfilling the Nyquist criterion, too. To address errors caused by leakage, we used the Kaiser window, which was chosen empirically.

2.3 Feature extraction

The third step is comparing the PSDs of the activity time sequences to each other by the extraction of well-known statistical features. These features provide new periodicity information about the activity time sequences. Using these we can compare the surgeon's activities. The following five features are calculated for every considered activity sequence: Total Power (is the sum of the intensity), Dominant Frequency (is the frequency of maximum power in the PSD.), Mean Frequency (is calculated as the sum of product of the power spectrum and the frequency divided by the total sum of the power spectrum.) and the Median Frequency (is the first frequency which exceeds half of the power of the spectrum.).

2.4 Comparison of surgical activities

Finally the frequency-based similarities of several surgical workflows of a specific surgery type were calculated with regard to their activity time sequences. For this purpose the surgical workflows of every single activity time series were chosen from those activity sequences which had the smallest deviation of the calculated features' values to each other.

Figure 1: The remaining intervention time error of the neurosurgical intervention lumbar discectomy in relation to the surgical phase. Green marked areas were an accurate predictor in special phases. Yellow marked areas were accurate predictors for the whole surgical procedure. Grey marked areas were not recorded in these surgical phases.

Surgical activity	Mean prediction intervention error				
	Intervention phase			Whole intervention	
	preparartion	discectomy	closure		prediction error in %
bodypart					
left hand	26 min 25 s ± 35 min 48 s	39 min 15 s ± 19 min 10 s	10 min 37 s ± 6 min 2 s	45 min 3 s ± 32 min 50 s	36.41
right hand	29 min 57 s ± 38 min 32 s	36 min 35 s ± 20 min 6 s	9 min 27 s ± 6 min 8 s	41 min 39 s ± 33 min 52 s	33.66
used instrument					
scissors	23 min 7 s ± 37 min 17 s	21 min 39 s ± 8 min 31 s		46 min 34 s ± 35 min 25 s	37.64
scalpel	27 min 23 s ± 38 min 42 s	40 min 58 s ± 15 min 10 s		50 min 15 s ± 32 min 5 s	40.62
forceps	28 min 35 s ± 35 min 41 s	36 min 38 s ± 19 min 54 s	9 min 39 s ± 6 min 11 s	43 min 39 s ± 33 min 7 s	35.28
retractor	19 min 17 s ± 38 min 4 s	36 min 17 s ± 20 min 16 s	10 min 52 s ± 6 min 41 s	42 min 3 s ± 33 min 33 s	33.98
suction	24 min 45 s ± 34 min 26 s	39 min 48 s ± 18 min 0 s	11 min 52 s ± 6 min 42 s	46 min 40 s ± 32 min 15 s	37.71
curettes	9 min 58 s ± 13 min 17 s	11 min 46 s ± 3 min 16 s		20 min 1 s ± 12 min 24 s	16.18
dissectors	23 min 57 s ± 36 min 50 s	36 min 15 s ± 20 min 23 s		48 min 58 s ± 32 min 47 s	39.57
drape	58 min 30 s ± 34 min 58 s		2 min 35 s ± 0 min 55 s	73 min 49 s ± 42 min 1 s	59.66
thread			10 min 34 s ± 6 min 4 s	10 min 34 s ± 5 min 58 s	8.54
cottonoids	28 min 23 s ± 17 min 12 s	44 min 29 s ± 12 min 45 s	9 min 25 s ± 7 min 43 s	41 min 3 s ± 20 min 54 s	33.18
hook	22 min 58 s ± 35 min 45 s	36 min 48 s ± 19 min 33 s		50 min 40 s ± 32 min 10 s	40.95
rongeurs	23 min 8 s ± 38 min 56 s	36 min 20 s ± 20 min 25 s		47 min 40 s ± 33 min 50 s	38.52
forceps coagulated	25 min 53 s ± 38 min 24 s	38 min 1 s ± 18 min 39 s	3 min 20 s ± 1 min 41 s	45 min 26 s ± 33 min 43 s	36.71
action					
swab	26 min 38 s ± 16 min 45 s	26 min 57 s ± 0 min 57 s	46 s ± 3 s	40 min 47 s ± 19 min 53 s	32.96
cut	27 min 4 s ± 36 min 31 s	41 min 21 s ± 14 min 22 s		51 min 25 s ± 30 min 33 s	41.55
hold	28 min 30 s ± 35 min 59 s	39 min 56 s ± 17 min 57 s	10 min 45 s ± 5 min 55 s	45 min 10 s ± 32 min 35 s	36.50
install	24 min 19 s ± 35 min 49 s	36 min 6 s ± 20 min 17 s	8 min 24 s ± 6 min 22 s	43 min 45 s ± 33 min 45 s	35.36
dissect	23 min 57 s ± 38 min 25 s	36 min 8 s ± 19 min 58 s		47 min 46 s ± 33 min 27 s	38.61
remove	23 min 8 s ± 39 min 18 s	36 min 22 s ± 19 min 42 s	11 min 10 s ± 6 min 31 s	41 min 31 s ± 33 min 50 s	33.56
drill	34 min 14 s ± 14 min 44 s	5 min 59 s ± 0 min 0 s		38 min 37 s ± 20 min 11 s	31.20
use	17 min 17 s ± 21 min 55 s	13 min 51 s ± 3 min 47 s		33 min 22 s ± 22 min 41 s	26.96
irrigate	14 min 42 s ± 10 min 16 s	39 min 19 s ± 18 min 42 s	9 min 35 s ± 3 min 40 s	**26 min 33 s ± 18 min 4 s**	**21.45**
suture			10 min 40 s ± 6 min 2 s	10 min 40 s ± 5 min 56 s	8.62
anatomical structure					
fascia	20 min 55 s ± 38 min 29 s		11 min 28 s ± 6 min 40 s	44 min 47 s ± 38 min 31 s	36.20
dura	29 min 29 s ± 15 min 39 s	18 min 33 s ± 6 min 49 s	11 min 23 s ± 7 min 55 s	32 min 17 s ± 19 min 46 s	26.09
muscle	23 min 55 s ± 36 min 47 s	40 min 42 s ± 16 min 58 s	11 min 6 s ± 6 min 29 s	44 min 33 s ± 32 min 20 s	36.00
skin	29 min 45 s ± 38 min 1 s		11 min 54 s ± 6 min 18 s	45 min 16 s ± 38 min 13 s	36.58
vertebra	29 min 21 s ± 35 min 2 s	41 min 41 s ± 17 min 43 s		50 min 59 s ± 30 min 5 s	41.20
ligament	23 min 8 s ± 36 min 50 s	35 min 22 s ± 20 min 43 s	9 min 44 s ± 6 min 8 s	42 min 44 s ± 33 min 44 s	34.54

3 Experiments and results

3.1 Evaluation

Our four step study was performed based on forty recorded surgical workflows of lumbar discectomies. The four steps were further explained in section 2. The surgical workflows used, were manual recordings from the ICCAS from 2007 and represent lumbar discectomies conducted by surgeons with various skill levels; the neurosurgical workflows were divided into several surgical phases: approach to disc (preparation), discectomy and closure. The cross leave-one-out validation was started one minute after the cut time of a surgical procedure and the examined interval increased by one minute of the intervention time. Based on the prediction of the remaining intervention time error the several activities were compared. The maximum durations of the different phases were varied; the duration declined from the preparation phase to the final surgical phase.

3.2 Results

In our evaluation study the predicted remaining intervention time error was calculated to investigate the feasibility of a frequency based activity comparison. The prediction error of activities which had the *curettes* as used instrument in the preparation phase, those which had the *drill* as used instrument in the discectomy phase and those with the *drape* as used instrument in the closure phase had the best outcomes. The activity *irrigate* had a very low prediction error of 21.45% in relation to the maximum possible error and had the smallest mean prediction error (26 min 33s). However, many activities such as those identified by being conducted with the surgeon's *right* and *left hand* of the neurosurgical intervention exhibited high fluctuations which are depicted in the large standard deviation and asymmetric distribution.

Small standard deviation was seen for activities that were performed with *cottonoids* or a *drill*. Moreover, the mean prediction error showed a marked increase for many activities performed on the *muscle* or *vertebra* of the patient and for *cutting* in the discectomy phase. On the contrary, surgical activities such as those performed on the patient's *dura* unveiled a decrease of prediction error as the intervention progressed.

4 Discussion and conclusion

In this work we investigated every surgical activity during interventions of a specific surgery type based on spectral estimation. The periodogram as nonparametric spectral estimation was calculated. To obtain the significance of every activity we considered the predicted intervention time error of every surgical activity.

The activity *irrigate* had the best outcome with a mean prediction error of 26 min 33 s. The needed activity information could be provided by an integrated and networked OR based on the signals of an irrigation pump. The drawback is that the ascertained significance is only valid for lumbar discectomies. Thus, a more general available activity would be more significant. The activities of the surgeon's *right* and *left hand* are applicable in a wider range of surgery types. The mean prediction error for activities performed with the *right hand* was 41 min 39 s and for those done with the *left hand* 45 min 3 s. Furthermore a disadvantage is the wide variance of prediction error over intervention time. The high standard deviation can be inferred by the long time and by surgical workflow dependencies of the presented method. The influence of the time of the recording and the influence of the type of workflow that was used have to be investigated more deeply in future works. Additionally further studies have to investigate methods of decreasing fluctuation. The presented method showed a novel approach to compare surgical activities with regard to their similarity. Hence, the presented method can be applied in an effective resource and time management system [17]. The presented method exhibits feasibility for being integrated in assistance systems and thereby enhancing the daily routine inside the OR. Furthermore, the documentation during surgeries can be enhanced e.g. by automatically generated post-operative reports.

Author's Statement
Conflict of interest: Authors state no conflict of interest. Material and Methods: Informed consent: Informed consent has been obtained from all individuals included in this study. Ethical approval: The research related to human use has been complied with all the relevant national regulations, institutional policies and in accordance the tenets of the Helsinki Declaration, and has been approved by the authors' institutional review board or equivalent committee.

References

[1] K. Cleary and A. Kinsella, "OR 2020: the operating room of the future," *Journal of laparoendoscopic & advanced surgical techniques. Part A*, vol. 15, no. 5, pp. 495, 497-573, 2005.
[2] H. U. Lemke and M. W. Vannier, "The operating room and the need for an IT infrastructure and standards," *Int J CARS*, vol. 1, no. 3, pp. 117–121, 2006.
[3] J. V. Sutherland, van den Heuvel, Willem-Jan, T. Ganous, M. M. Burton, and A. Kumar, "Towards an intelligent hospital environment: OR of the future," *Stud Health Technol Inform*, vol. 118, pp. 278–312, 2005.
[4] J. G. Wright, A. Roche, and A. E. Khoury, "Improving on-time surgical starts in an operating room," *Can J Surg*, vol. 53, no. 3, pp. 167–170, 2010.
[5] B. Denton, J. Viapiano, and A. Vogl, "Optimization of surgery sequencing and scheduling decisions under uncertainty," *Health Care Manag Sci*, vol. 10, no. 1, pp. 13–24, 2007.
[6] N. Padoy, T. Blum, S.-A. Ahmadi, H. Feussner, M.-O. Berger, and N. Navab, "Statistical modeling and recognition of surgical workflow," *Med Image Anal*, vol. 16, no. 3, pp. 632–641, 2012.
[7] S. Franke, J. Meixensberger, and T. Neumuth, "Intervention time prediction from surgical low-level tasks," *Journal of Biomedical Informatics*, vol. 46, no. 1, pp. 152–159, 2013.
[8] B. J. Ammori, M. Larvin, and M. J. McMahon, "Elective laparoscopic cholecystectomy: preoperative prediction of duration of surgery," *Surg Endosc*, vol. 15, no. 3, pp. 297–300, 2001.
[9] R. Alvarez, R. Bowry, and M. Carter, "Prediction of the time to complete a series of surgical cases to avoid cardiac operating room overutilization," *Can J Surg*, vol. 57, no. 11, pp. 973–979, 2010.
[10] L. Riffaud, T. Neumuth, X. Morandi, C. Trantakis, J. Meixensberger, O. Burgert, B. Trelhu, and P. Jannin, "Recording of surgical processes: a study comparing senior and junior neurosurgeons during lumbar disc herniation surgery," *Neurosurgery*, vol. 67, no. 2 Suppl Operative, pp. 325–332, 2010.
[11] G. Forestier, F. Lalys, L. Riffaud, B. Trelhu, and P. Jannin, "Classification of surgical processes using dynamic time warping," *Journal of Biomedical Informatics*, vol. 45, no. 2, pp. 255–264, 2012.
[12] T. Blum, H. Feussner, and N. Navab, "Modeling and segmentation of surgical workflow from laparoscopic video," *Med Image Comput Comput Assist Interv*, vol. 13, no. Pt 3, pp. 400–407, 2010.
[13] Bohn S, Lindner D, Franke S, Neumuth T, "An interoperability architecture for networked medical devices and its application to neurosurgery," in *The 15th International Conference on Biomedical Engineering (ICBME 2013), Singapore*, 2013.
[14] T. Neumuth, F. Loebe, and P. Jannin, "Similarity metrics for surgical process models," *Artificial intelligence in medicine*, vol. 54, no. 1, pp. 15–27, 2012.

[15] A. Schuster, "On the investigation of hidden periodicities with application to a supposed 26 day period of meteorological phenomena," *J. Geophys. Res*, vol. 3, no. 1, p. 13–13, 1898.
[16] P. A. Lynn and W. Fuerst, *Introductory digital signal processing with computer applications*, 2nd ed. Chichester [u.a.]: Wiley, 1998.
[17] C. Herfarth, "'Lean' surgery through changes in surgical work flow," *The British journal of surgery*, vol. 90, no. 5, pp. 513–514, 2003.