Situation Detection for an Interactive Assistance in Surgical Interventions Based on Random Forests

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1 Purpose

In contemporary medicine, the use of assistance functions for diagnosis and surgical interventions is an evolving area (*5*). These functions can help to master medical challenges like the prevention of treatment errors, enhancement of outcome and the preservation of a high level of satisfaction for employees as well as patients.

To enable such assistance functions in a surgical intervention, we propose a situation detection based on Random Forests. More precisely, the progress of an intervention is deduced by detecting single surgical steps of a pre-modeled workflow. We are convinced, that among other things – e.g. the status of the operating team – this information is a keystone to carry out a tailored assistance function.

2 Methods

We have chosen supervised learning (*3*) for training the models that are used for the detection of the actual progress of a surgical intervention. The idea of supervised learning is to build models which are able, after a learning phase, to deliver correct target vectors $\{t_1, t_2, t_3 ... t_n\}$ for new, previously unseen, input vectors $\{x_1, x_2, x_3 ... x_n\}$. To do so the learning phase needs different input and corresponding target vectors which a significant for the identification of steps inside the workflow.

12 datasets of a simplified workflow with 7 surgical steps were recorded and labeled manually. The re-enacted surgical steps differ in the use of tracked instruments, number and position of persons. In Fig. 1 a detailed characteristic of each surgical step is presented. For the implementation of the probabilistic models we decided to use Random Forests as presented in (*4*) and Support Vector Machine to evaluate the results.

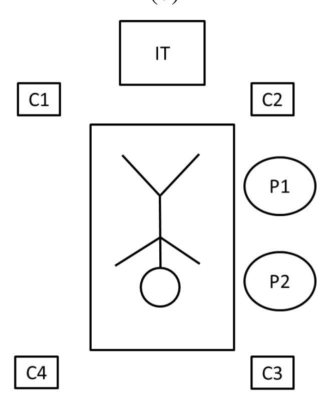
For the recording and a future online identification we have choose the OP:Sense Setup (*2*) and the corresponding perception system (*1*). The perception system partly comprised of four Kinect V1 ™ whereby it is possible to recognize people as well as objects in operation theatre. The algorithms outcome delivers the current position of each person, it's trace on the floor, as well as a representation as a point cloud and skeleton tracking from multiple viewpoints. In the presented approach especially the skeleton tracking deploys data of the characteristic positing of each person in the operation theatre and the total amount of persons. For the identification of the instruments we used ART, a marker based tracking system.

Figure 1: Specification of the workflow. Subfigure (a) shows the characteristic of the surgical steps a-g. Subfigure (b) depicts the positioning of the operating team in a so called 'normal positioning'. This position is taken up by the team members in steps a-c and f-g. During the switching, person 1 (P1) and person 2 (P2) change their positing. C1 to C4 are representing the camera positions on the ceiling. IT is the instrument table where the different instruments are placed at the beginning.

(a)

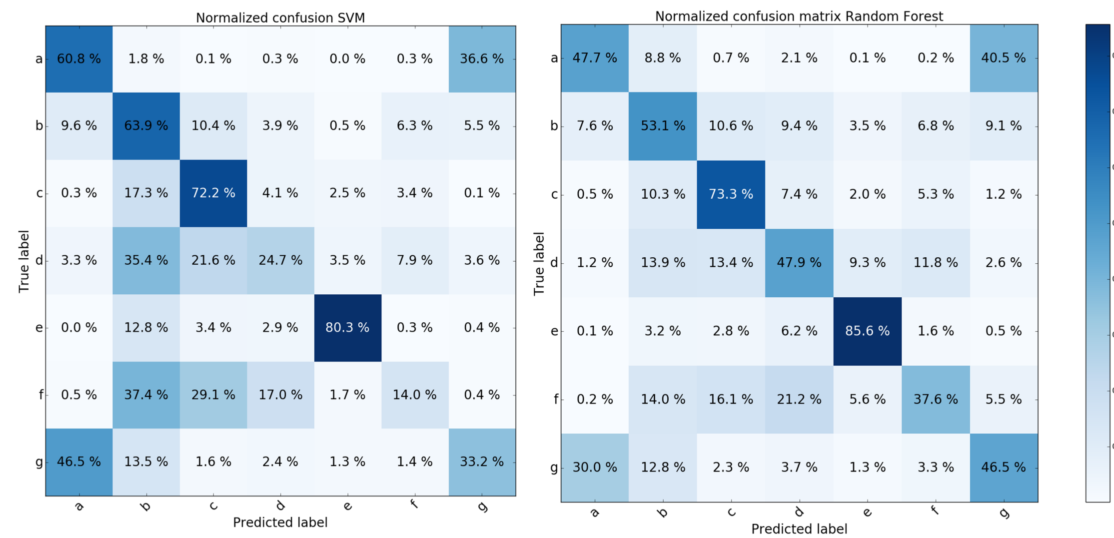
		Surgical steps						
Feature	**Specification**	**a**	**b**	**c**	**d**	**e**	**f**	**g**
Positioning of the operation team	Normal	x	x	x			x	x
	Switched				x	x		
Number of person at operating table	1	x						x
	2		x	x	x	x	x	
Number of used instruments	0	x	x		x		x	x
	1			x				
	2					x		

(b)



3 Results

To evaluate the performance of the method we used cross-validation with a leave-one-out iterator on the 12 datasets. Thereby each dataset is used once as a test-set while the remaining dataset are for the training set. In Fig. 2 the corresponding normalized confusion matrix are presented. The diagonal elements representing the amount for which the predicted label is equal to the true label, while off-diagonal elements are mislabelled by the classifier. It can be seen the random forest classifier identify most of states.



(a) SVM (b) Random Forest

Figure 2: Confusion Matrix based on cross validation and leave one out

4 Conclusion

In this work we introduced a situation detection to enable an interactive assistance during a surgical intervention. We are convinced, that the current progress of an intervention is essential for providing a tailored assistance function.

Therefore, we trained Random Forests to detect 7 different surgical steps of a re-enacted intervention. Both classifier mixed up often the states *a* and *g*. One of the reasons for this can be found in the specification of the both states which are indeed similar. In comparison to the Random Forest classifier the SVM identified more often false state as true, e.g. state *d*, *r* and *f*.

It can be summarized that the results seems to be promising – Random Forests performed well in the given classification task.

For the future, we plan to take our approach to the next level, by combining the classification results with indicators of the operating team status. This will be the starting point for a targeted assistance function.

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References and Notes

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