Cascade analysis for intestinal contraction detection

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Abstract. In this work, we address the study of intestinal contractions in a novel approach based on a machine learning framework to process data from Wireless Capsule Video Endoscopy. Wireless endoscopy represents a unique way to visualize the intestine motility by creating long videos to visualize intestine dynamics. In this paper we argue that to analyze huge amount of wireless endoscopy data and define robust methods for contraction detection we should base our approach on sophisticated machine learning techniques. In particular, we propose a cascade of classifiers in order to remove different physiological phenomenon and obtain the motility pattern of small intestines. Our results show obtaining high specificity and sensitivity rates that highlight the high efficiency of the selected approach and support the feasibility of the proposed methodology in the automatic detection and analysis of intestine contractions.

Keywords: intestine video analysis, anisotropic features, support vector machine, cascade of classifiers

1. Introduction

The analysis of the intestinal contractions, in particular the number, frequency and distribution along the intestinal tract, represents one of the methods with the highest clinical significance for diagnosing several intestinal dysfunctions [1]. Some myopathic diseases have been associated with functional abnormalities of the intestines, weak intestinal contractions and gastrointestinal dysfunctions. Small intestinal manometry is widely accepted as the most reliable technique for motility analysis so far [2]. However, this approach is an invasive test which carries discomfort problems for the patient. On the other hand, it suffers a lack of sensitivity over certain types of contractions.

Several works have reported the support of automatic systems for diagnosis of different pathologies, such as ulcer or cancer, with applications based on digital image analysis and processing [5-9]. As far as we know, no preceding work has been reported on computerized analysis of capsule video endoscopy for the automatic identification of specific motility events such as intestinal contractions, making this novel framework a challenging and open field of research.

In this work, we address the study of intestinal contractions in a novel approach using Wireless Capsule Video Endoscopy (WCVE) as data source (Given Imaging, Yoqneam, Israel) [3][4]. WCVE consists of a capsule with a camera, a battery and a set of led lamps for illumination attached to it, which is swallowed by the patient, emitting a radio frequency signal that is received in an external device. Fig.1 shows three examples of intestine contractions acquired by the WCVE. The visualization and precise interpretation of the capsule recordings is straightforward, but it is time consuming and stressful, since the prevalence of contractions in video is very low (1:50 frames). Due to the large amount of data generated by the WCVE, developing techniques for automatic analysis of the videos is of high interest in order to ease the work of the physicians in the daily clinical practice.

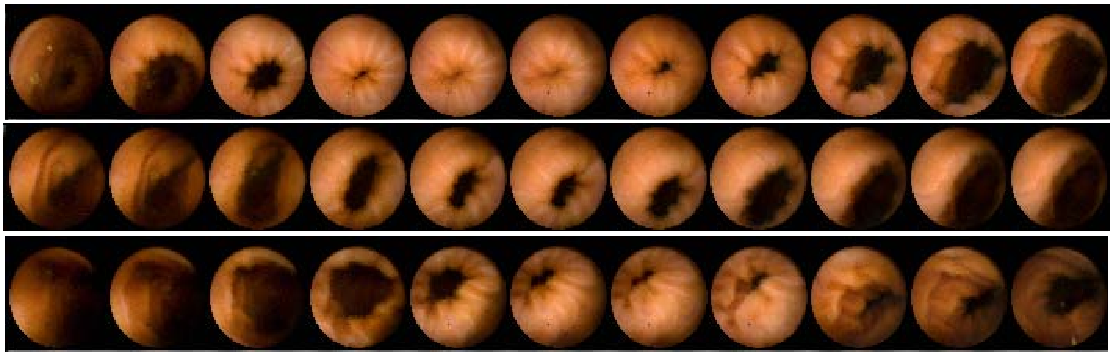

Fig.1 Three examples of intestine contractions

Our proposal is based on a machine learning system which automatically learns and classifies contractions from a capsule video source, providing the expert with a subset of the video sequences which are highly likely to contain intestinal contractions. This yields to a considerable reduction in visualization time, and the consequent reduction of stress, since most of the sequences to be analyzed are real contractions. In addition, one of the main advantages of our system is related to its ability to dynamically adapt itself to the different patterns of intestinal activity associated with intestinal contractions.

2. Methodology

Our system is deployed in a sequentially modular way, namely, a cascade. Each part of the cascade receives as an input the output of the previous stage. The main input consists of the video frames, and the main output consists of the frames suggested as contractions. The rejected frames are distributed among three different stages: a first pre-processing stage, where motion pattern is detected; a second stage, where not valid for analysis frames with poor visibility is disregarded due to turbid content or displacement of the camera are rejected; and a final classification stage based on a support vector machine [10], where the final output is provided as suggested contractions. The learning steps of each stage of the cascade involve a set of parameters for tuning the classification performance. The turbid frames step and the final classification step consist of two support vector machine classifiers trained with a data set which has been labeled from previous studies.

The choice of the cascade system is underpinned by the fact that each step is designed in order to reject an amount of frames which mainly include images which are not to be intestinal contractions -i.e., the system negatives-, letting pass through the sequential stages those frames related to intestinal contractions -i.e., the system positives-. This yields to an effective reduction of the imbalance ratio of the data set at the input of the last classification stage. In our strategy, each stage is tuned to prune as many non-contraction frames as possible, trying to minimize the loss of true positives, and achieving in this way an effective reduction in the imbalance ratio of the data. The last stage of the cascade, consisting of the support vector machine classifier trained by means of under-sampling, implements a classification problem with an imbalance ratio about 1:5 –in contrast with the 1:50 at the input of the system-. Fig.2 shows the detected contractions of a video, the central frame of the contraction is depicted in green. The top time line shows the temporal distribution of contractions along the capsule movement.

Fig.2 Final result of the cascade system for contraction detection

3. Results

Our experimental tests were performed using 10 videos obtained from 10 different fasting volunteers, aged between 22 and 33, at the Digestive Diseases Dept. of the University Hospital “Vall d'Hebron” in Barcelona, Spain. The endoscope capsules used were developed by Given Imaging, Ltd., Israel [11]. For each studio, one expert visualized the whole video and labeled all the frames showing intestinal contractions between the proximal jejunum and the first cecum images. These findings were used as the gold standard for testing our system. Performance results were evaluated for each studio following the leave-one-out strategy: one video was separated for testing while the 9 remaining videos were used for training the SVM classifiers using under-sampling.

The global performance of the system, viewing all the steps in the cascade as a whole black box, can be faced in multiple ways. Our approach achieves an overall sensitivity of 70.02%, picking 80% for the study referred as Video 1. The high overall specificity value of 99.59% is typical of imbalanced problems, and for this reason it is not generally useful for performance assessment tasks. However, FAR and precision carry out insightful information about what the output is like. The resulting precision value of 59.91% tells us that 6 out of 10 frames in the output correspond to true findings. FAR is similar, but in terms of noise (the bigger the FAR, the larger the number of false positives), and normalized by the number of existing contractions. For different videos providing an output with a fixed precision, those with the highest number of findings in video will have lower FAR. In this sense, a FAR value of one tells us that we have obtained as many false positives as existing contractions in video. The sequences display the inherent difficulty related to the high variability of patterns present at the output of the system: the lateral movement of the camera while focusing the lumen which can be confused with the pattern of its contraction, the differences in illumination creating shadows which can be confused with the lumen, and the residual presence of patterns of turbid liquid, share the main responsibility in the false positives.

4. Conclusions

This work addressed the problem of the automatic detection of intestinal contractions in capsule video endoscopy, a novel and highly challenging issue in medical imaging. We showed the design of the system in terms of sequential stages to be helpful from a two-fold perspective: on one hand, this approach lets the experts to identify different features related to intestinal motility in capsule video endoscopy, such as the presence of high content of intestinal juices which hinders the video visualization, or the detection of spans of time with no motility activity. Using this modular perspective, domain knowledge can be easily added to the system by the experts, by means of the inclusion of new sequential stages to the cascade. On the other hand, we showed the rejection of negatives in a sequential way to be a useful strategy for dealing the skewed distribution of positives -i.e., contractions- and negatives -i.e., non-contractions- along the video data. We provided a detailed explanation and study of the different steps we defined in the cascade, showing intermediate measures of performance for each stage.

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