Detection of Unsafe Action from Laparoscopic Cholecystectomy Video

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ABSTRACT
Wellness and healthcare are central to the lives of all people, young or old, healthy or ill, rich or poor. New computing and behavioral research can lead to transformative changes in the cost-effective delivery of quality and personalized healthcare. Also beyond the daily practice of healthcare and wellbeing, basic information technology research can provide the foundations for new directions in the clinical sciences via tools and analyses that identify subtle but important causal signals in the fusing of clinical, behavioral, environmental and genetic data. In this paper we describe a system that analyzes images from the laparoscopic videos. It indicates the possibility of an injury to the cystic artery by automatically detecting the proximity of the surgical instruments with respect to the cystic artery. The system uses machine learning algorithm to classify images and warn surgeons against probable unsafe actions.

Categories and Subject Descriptors
I.4.0 [**Image Processing and Computer Vision**]: General – *Image processing software*; J.3 [**Computer Applications**]: Life and Medical Sciences – *biology and genetics*.

General Terms
Algorithms, Measurement, Design, Experimentation, Theory

Keywords
Situation-awareness, laparoscopic cholecystectomy, image processing, machine learning.

1. INTRODUCTION
Context-aware computing has emerged over the last few years, as a promising way to build intelligent and dynamic systems in overall computer science areas such as ubiquitous computing [2]. Recently the concept of situation-awareness is focused beyond the context-awareness. Situational awareness" simply means understanding the current situation [3]. It is the ability to look at a huge variety of data, determine what is relevant, synthesize the data, and act on it. In health care, situational awareness is the ability to collect the correct medical information, analyze it, and project what will come next, so the appropriate actions can be taken. Surgery, which is one of the most complicated, time-critical and high-pressure medical practice, is an excellent candidate for development of such systems.

In an ongoing research with colleagues at University of Maryland Medical Center (UMMC) and IBM Toronto Labs, we are developing a situation-aware computing system for operating room. As part of this system we have developed a module that detects and indicates potential unsafe actions while a surgery is being performed.

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2. BACKGROUND AND MOTIVATION
Traditionally, the surgical staff was responsible for monitoring different activities within an operating room. However there are multiple data sources in an operating room and it is difficult to monitor and analyze all the data streams arriving from sensors, services and devices.

Our system aims at easing the burden on the surgical staff by automatically detecting potentially unsafe actions from surgeries. In the prototype developed, we focus on a particular type of surgery – laparoscopic cholecystectomy. This system can also aid surgical training by giving feedback to trainee surgeons when they accidentally perform a potentially hazardous action. This eliminates the need for continuous human supervision for laparoscopic surgical training.

Laparoscopic surgery [4] is a modern surgical technique in which operations in the abdomen are performed through small incisions. The key element is the laparoscope – a thin, rigid tube which has a camera at its tip.

2.1 Cholecystectomy
Cholecystectomy is the surgical removal of gall bladder. The operation is done to remove gallstones or an infected or inflamed gallbladder.

Laparoscopic cholecystectomy has now replaced open cholecystectomy as the first-choice of treatment for gallstones and inflammation of the gallbladder unless there are contraindications to the laparoscopic approach. In this procedure three to four incisions are made in the abdomen, each approximately 1/2" in length. These incisions allow the insertion of operating ports, small cylindrical tubes approximately 5-10 mm in diameter through which surgical instruments can placed into the abdominal cavity. One incision is made around the navel and the other three are areas around the abdomen. Carbon dioxide gas is used to inflate the abdomen. The physician uses a laparoscope, a thin, rigid viewing tube to navigate through the organs and assist in removing the gallbladder. The laparoscope is inserted into the incision by the navel. Images taken by the scope are reflected on video monitors in the operating room, giving the surgeon a close-up view of the organs and tissues.. The other three incision are used to insert other instruments, which grasp, clamp and cut free the gallbladder from its attachments. The gallbladder is cut away using either a laser or electrocautery device; both of which use localized heat to minimize bleeding. Once the gallbladder has been cut free, it is drained of bile, collapsed and removed through the navel incision.

Ancona *et al*. [5] describes the analysis of various risk factors in data from 100 consecutive patients who underwent laparoscopic surgery. In spite of factors like age, obesity the benefits of laparoscopic cholecystectomy over open surgery were clearly evident: less discomfort, shorter hospital stays with quicker recovery time, reduced postoperative pain, smaller scars.

2.2 Injuries in Laparoscopic Cholecystectomy

Laparoscopic cholecystectomy is surgically demanding and introduces specific risks unique to the laparoscopic surgery that are not present during the performance of procedures like open cholecystectomy. Alarmed by a high number of severe complications found after laparoscopic cholecystectomy, a review was conducted for this practice. It led to the identification of 158 serious complications as against 23 in open cholecystectomy [6]. Serious complications that occur with laparoscopic cholecystectomy are common bile duct injury, major vessel laceration, hemorrhage, bile leak, bowel perforation, trocar injury, liver injury and stray electrosurgical burns [7]. One such injury to be avoided is injury to the cystic artery, the blood vessel that supplies oxygenated blood to the gallbladder. Uncontrolled bleeding from the cystic artery and its branches is a serious problem that may increase the risk of intraoperative lesions to vital vascular and biliary structures [8]. These complications result in part from surgical inexperience and the technical constraints that are inherent to the minimally invasive approach.

2.3 Safety Measures in LapChole

Various ways have been researched to improve safety in laparoscopic cholecystectomy. A "safety zone" of operation is introduced by Taniguchi *et al.* [9] to ensure the cystic duct, cystic artery are exposed near the gallbladder's neck. The observance of the rule of "keep operating in the safety zone" reduces bile duct injury and the rate of conversion to open surgery. Almutairi *et al.* [10] describes a safe triangle of dissection to prevent misidentification of common bile duct during dissection of Calot's triangle. In addition to these methods, there has been emphasis on improving the surgeon's techniques and performance. A range of simulation devices are used to train surgeons through repetitive proctored challenges. They enable detection and analysis of surgical errors and near miss incidents without risk to patients. Minimally invasive surgical trainers with virtual reality are used to identify errors, quantify them and monitor surgical performance.

2.4 Context awareness in Health Care

Health care evolves as new technologies are adopted. Aspects such as context awareness help health care professionals to shift part of their activities to machines. Dey *et al.* [11] proposed a definition of context which is the following: “Any information that can be used to characterize the situation of entities (i.e. whether a person, place or object) that are considered relevant to the interaction between a user and an application, including the user and the application themselves. Context is typically the location identity and state of people, groups and computational and physical objects”. Kjeldskov *et al.* [12] defines context-aware computing as “an application’s ability to adapt to changing circumstances and respond according to the context of use”. Context awareness is a concept that has been described for some time, but technologies such as wireless technologies, mobile tools, sensors, wearable instruments, intelligent artifacts, handheld computers are now available to support the development of applications. Healthcare systems use context-aware computing to explore new tools as well as propose and develop useful and acceptable solutions. Intensive-care units, operating rooms contain complex health care situations making it a challenging area for such systems. Systems in intelligent operating rooms (ORs) determine actual context from the environment by means of smart sensors embedded in the environment. The data obtained from these sensors could be used to infer, for example, information about the current task of the surgeons, nurses based on their within the hospital, the time of day, their schedule for the day, and with whom they are in close proximity. Such systems help health care professionals to manage their tasks while increasing the quality of patient care. Ordóñez et al. [13] describes a context-aware environment to provide improved surgical training. The system tracks low level events in the training room and derives a training context based on them.

2.5 Situation Awareness in Laparoscopic Surgery

Intelligent systems have being developed to automatically analyze surgical workflow which is important an important aspect for assessment of surgical skills. These systems need to be aware of the current state of the ongoing surgery. Such systems are called "situation-aware" systems. Situation awareness” simply means understanding the current situation. The system infers the “situation” or state of the surgical process by using the various inputs from the sensors, monitoring systems, a live video recording of the surgical field and a broader view of the OR from another video recording. Blum et al. [14] describes a system to model and analyze surgical workflow from laparoscopic videos. This approach models a surgery based on signals from uses reduced image feature space by using two different statistical models. It further segments a surgery into pre-defined phases and is able to identify those phases in a new surgery. Proper localization of the cystic artery is of great importance in laparoscopic cholecystectomy in order to ensure safe stapling and avoiding injury to the artery. Uncontrollable bleeding from the cystic artery is one of the main reason for conversion from laparoscopic to open cholecystectomy. In an evaluation study on 176 cases, cystic artery injury occurred in 5 (2.84%) cases. Bleeding could be controlled in 3 (1.70%) cases whereas 2 (1.14%) cases were converted [15]. Hemorrhage during laparoscopic cholecystectomy is usually more difficult to control than that during open cholecystectomy as blood tends to obscure the operative field [12]. Identification of the cystic artery is a time-consuming procedure especially for less experienced surgeons. Assessing technical skill during 30 operative procedures in a study showed that 5 (17%) procedures did not successfully complete all steps. In three of these patients, the step not completed was identification, ligation, and transection of the cystic artery [16]. Different advanced methods are applied in laparoscopic surgeries for detection of the blood vessels. These methods are complicated, and need expensive and highly technical medical equipments [17], [18]. The endoscopic pulse detector is a device that has been especially developed for detecting arteries in laparoscopy by an accelerometer on its tip. It is inexpensive and simple to use but requires the surgeon to temporarily stop the procedure and insert the device into the body and detect the artery [17]. Akbari et al. [18] describe an image-processing method for artery detection. The method detects the artery by sensing the change in movement of tissues over the artery based on the artery's pulsatile movement. These changes are detected from images captured at systolic and diastolic times.

Automated understanding of laparoscopic videos require tracking of surgical instrument. Previous research has tended to focus on tracking instruments with visual markers, but use of these type of markers have certain disadvantages. KcKenna et. al [19] describe a method for tracking surgical instruments in monocular endoscopic videos. This method uses pixel's color value as a discriminatory cue for whether or not it is occupied by a surgical instrument. It uses a generic model with two-dimensional shape constraints that are satisfied by the images of the instruments to be tracked.

3. SYSTEM DESIGN

By reviewing previous work, we can conclude that it is of high importance to avoid any injury to the cystic artery. An injury to cystic artery can cause uncontrolled bleeding and require conversion of laparoscopic cholecystectomy to open cholecystectomy. Blood hemorrhage during laparoscopic cholecystectomy is usually more difficult to control than that during open cholecystectomy as blood tends to obscure the operative field. Though advanced methods are applied for detection of blood vessels in laparoscopic surgeries, these methods are complicated and need expensive and highly technical medical equipments [17], [18]. The endoscopic pulse detector detects arteries in laparoscopy by an accelerometer on its tip. However it requires the surgeon to temporarily stop the procedure and insert the device into the body and detect the artery [17]. This may be done multiple times during the surgery requiring the surgeons to stop the procedure every time, thus causing inconvenience. The image-processing method for artery detection, described by Akbari et al. [18] requires additional information about the systolic and diastolic times. In real-time implementation, this would mean the BP monitor has to be synchronized with the system to detect if the image was captured at systolic or diastolic time. Our goal is to detect if the surgical instrument is close to the artery enough to pose a danger of rupturing it. Our method does not require any additional equipment for this purpose.

Our method simulated videos of laparoscopic cholecystectomy obtained from LAP Mentor ™ , which is a multi-disciplinary laparoscopic surgery simulator at University of Maryland Medical Center. We choose simulated videos because they have more comprehensive coverage of risky situation as compared to real videos. For better analysis we split the video into image frames with 3 channels of 8 bit each. We use a combination of global and local features representing the image. Global image features [20] are defined as those that are computed on the entire image, e.g., histogram representation of the image. As such only one signature is related to each image. Using global features the semantic gap between the low-level feature extraction by machine and the high-level scene interpretation by humans tends to be wide. Local features, on the other hand, are that computed at prominent image regions, e.g. texture or shape features localized at a particular image region. An assessment is made by Tagare et al. stating that the information contained in medical images is local [21], and hence, local features may narrow the semantic gap.

3.1 Reduction of Region of Interest

The first goal of our method is to narrow down on the part of image which has higher probability of presence of the cystic artery. This is part of the local image feature extraction. For this we first detect the neck of the gallbladder. The gallbladder has four areas - the fundus, body, infundibulum and neck [22]. The body of gall bladder extends from the fundus into the tapered portion or neck which curves to terminate in the cystic duct as shown in Fig. 1 [23]. The arteries of the gallbladder are derived from cystic branch of hepactic artery. The cystic artery arises from the right hepatic artery 95% of the time [22] and courses the neck of the gallbladder. So we focus on identifying the neck of the gall bladder where it joins the cystic duct.

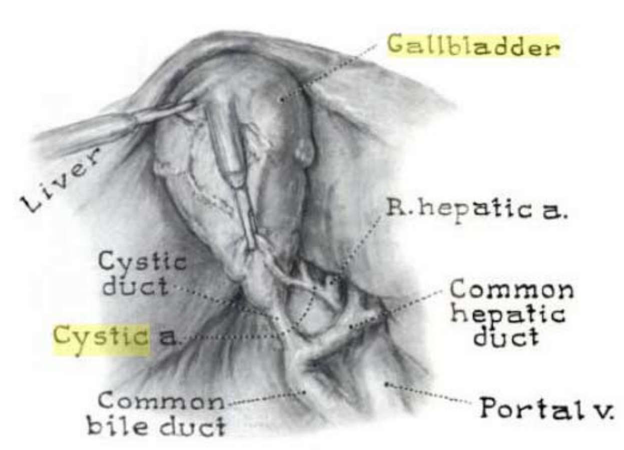


Figure 1. Exposure of Calot's triangle by retraction of dome of the gallbladder towards the right shoulder and the infundibulum towards the right of the patient, thus exposing the cystic and common bile ducts. [23]

To achieve this we perform template matching using normalized squared difference matching method. An image patch, containing the portion of neck of gallbladder where it joins the cystic duct, is used. This patch is matched against each input image from the video by sliding it over the input image using normalized squared difference matching. The squared difference method takes the squared difference between the patch and image. A match is 0 and bad matches are large values. We use *I* to denote the input image, *T* the template or patch, and *R* the result.

$$R_{\text{sq.diff}}(x, y) = \sum_{x', y'} (T(x', y') - I(x + x', y + y'))^2$$

The normalized method helps reduce the effects of lighting differences between the template and the image. The normalization coefficient is:

$$Z(x,y)=\sqrt{\sum_{x',y'} T(x',y')^2 \cdot \sum_{x',y'} I(x+x',y+x')^2}$$

Hence for normalized squared difference method of template matching:

$$R(x,y)=\frac{\sum_{x',y'}(T(x',y')-I(x+x',y+y'))^2}{\sqrt{\sum_{x',y'}T(x',y')^2\cdot\sum_{x',y'}I(x+x',y+y')^2}}$$

We then search for the minimum and maximum element values and their positions in the result obtained from template matching. This enables to find the location of the best match as shown (red rectangle) in Fig 2. The cystic artery courses the neck of the gallbladder and lies to the lower right side of the curve of the neck. Once we have the location of the neck of the gallbladder we use relative distance between the neck and cystic artery to find the region where the cystic artery is found. This is our region of interest (ROI) as shown (yellow rectangle) in Fig 2.

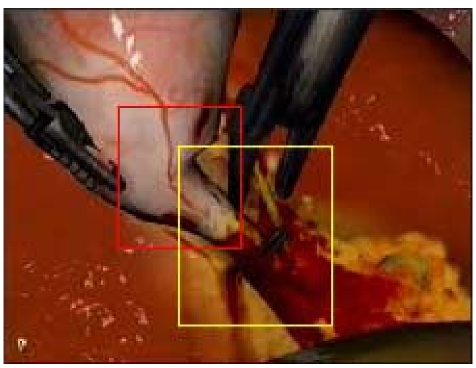


Fig 2. Result obtained after normalized squared difference template matching method.

3.2 Detection of Surgical Instruments

The next important goal is to detect the surgical instrument in the image.

In this method we smooth the original image using Gaussian blur method. This is part of the pre-processing of the image. Smoothing, also called blurring, is done to reduce image noise reduce details. Smoothing is also important when we wish to reduce the resolution of an image in a principled way. The visual effect of Gaussian blurring technique is a smooth blur resembling that of viewing the image through a translucent screen.

We convert the image obtained as a result of smoothing from RGB color space to HSV color space. The RGB model is mostly used in hardware oriented application such as color monitor. In the RGB model, images are represented by three components, one for each primary color – red, green and blue. Although human eye is strongly perceptive to red, green, and blue, the RGB representation is not well suited for describing color image from human perception point of view. Moreover, a color is not simply formed by these three primary colors. When viewing a color object, human visual system characterizes it by its brightness and chromaticity. The latter is defined by hue and saturation. Brightness is a subjective measure of luminous intensity. It embodies the achromatic notion of intensity. Hue is a color attribute and represents a dominant color. Saturation is an expression of the relative purity or the degree to which a pure color is diluted by white light. Value defines how light or dark a color is. The HSV model is motivated by the human visual system. Chen et al. [24] describe a study of different color representations. Experiments have shown that the features extracted from HSV color space, which decouples brightness from chromatic components, have demonstrated better performance than that from RGB color model. The features extracted in the HSV color space can capture the distinct characteristics of computer graphics better. The image obtained after converting the smoothened image into HSV color space is shown in Fig. 3.

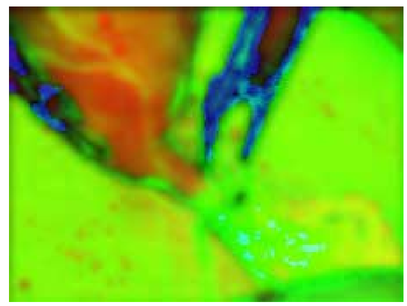


Fig. 3. Image representing HSV color space

The image contains 3 channels: hue, saturation and value. We split this multichannel image into 3 images with single channel. Following images Fig. 4.1 - 4.3 represent the individual channels.

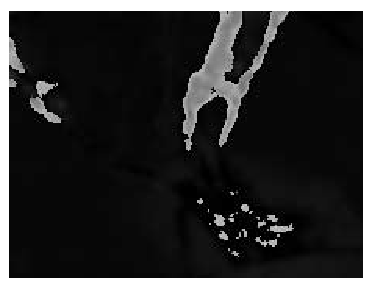
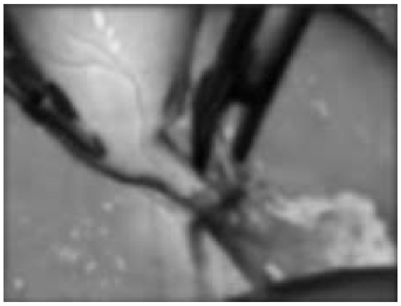


Fig. 4.1 Image representing hue channel from HSV image

Fig. 4.2 Image representing saturation channel from HSV image



Fig, 4.3 Image representing saturation value from HSV image

To isolate the surgical instruments in the image we need to eliminate all the anatomical structures, that act as noise, from the image. To achieve this, we threshold the images representing individual channels of HSV image. Thresholding is used for converting a grayscale or color image to a binary image based upon a threshold value. If a pixel in the image has an intensity value less than the threshold value, the corresponding pixel in the resultant image is set to black else it is set to white. The resultant image is binarized or has only two colors: black and white. We thus retain the significant part of the image and get rid of the unimportant part or noise. Fig, 5.1 – 5.3 show the binarized images obtained as a result of thresholding images Fig. 4.1 – 4.3.

Fig. 5.1 Image obtained after thresholding hue channel

Fig. 5.2 Image obtained after thresholding saturation channel

Fig. 5.3 Image obtained after thresholding value channel

The images obtained after thresholding show few traces of anatomical structure. We subject the images to another level of processing to maximize elimination of noise and accurately detect the surgical instrument in them. We use pixel-wise AND, XOR operation over the images to eliminates traces of anatomical structure from thresholded images.

Fig. 6 Image obtained after XOR-ing result of AND operation with thresholded saturation channel

As a final step towards isolating the surgical instrument in the image, we find contours to assemble the edge pixels of the elements in resultant image. This operation gives a better definition to the surgical instrument in the image as shown in Fig. 7

Fig.7 Image representing contours of surgical instrument

We now mark the region of interest (ROI) indicating location of cystic artery (Fig. 2) on the image representing contours of surgical instrument.

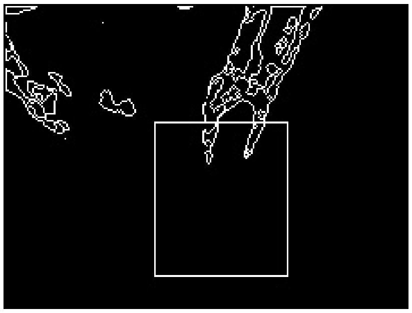


Fig. 8 Image representing region of interest (white rectangle) and contours of surgical instrument

3.3 Extraction of Global Image Features

All images can be represented by numerical features, which are extracted directly from the image pixels or by processing them. Local features of an image are defined as those that are computed at prominent image regions, such as texture or shape features localized at a particular image region [20]. This results in signatures, that are related to each image, focused on particular aspects of the image content. The information contained in medical images is local [21], and local features may narrow the semantic gap between low-level feature extraction by machine and the high-level scene interpretation by humans. The average pixel intensity of the region of interest in the image is an example of local feature of the image.

Global image features, are defined as those that are computed on the entire image, such as histogram representation of the image. The drawback in using global features the semantic gap between the low-level feature extraction by machine and the high-level scene interpretation by humans tends to be wide. To combine the best of both type of features we use a few global features along with the local feature we have extracted: average pixel intensity. The global features extracted from the images are: mean gray value, standard deviation, modal gray value, minimum and maximum gray value, center of mass, integrated density, median, skewness, kurtosis. In addition to these we use gray-level co-occurrence matrix (GLCM) which represents the distance and angular spatial relationships over an image. Each element of the GLCM is the measure of the probability of occurrence of two grayscale values separated by a given distance in given direction. We derive following textural features, called measures, from GLCM: angular second moment, contrast, correlation inverse, entropy, energy, inertia, homogeneity, prominence, variance and shade from each image.

4. EXPERIMENTAL ANALYSIS AND RESULTS

Our system was implemented using OpenCV image processing library for computer vision, to extract local feature. We used ImageJ, an image processing library to extract global features. ImageJ is a public domain, Java-based image processing program developed at the National Institutes of Health. It is widely used to display, edit, analyze and process 8-bit, 16-bit and 32-bit medical images having various formats. We used Weka, a machine learning tool, to analyze data and experiment with machine learning algorithms to classify images. Weka contains a collection of visualization tools and algorithms for data analysis and predictive modeling. It supports several standard data mining tasks, more specifically, data preprocessing, clustering, classification, regression, visualization and feature selection.

4.1 Feature Extraction and Selection

In image processing, feature extraction is a special form of dimensionality reduction. When the input data to an algorithm is too large to be processed and is suspected to be notoriously redundant (much data, but not much information) then the input data is transformed into a reduced representation set of features, called features vector. This transformation of the input data into the set of features is called feature extraction. The features extracted need to be carefully chosen so that the features set contains relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input. We use Jeffrey divergence to identify the best image features.

4.2 Jeffrey Divergence Metric

Jeffrey divergence is a statistical dissimilarity metric that can be used to compute the distance between class distributions of two values of the same feature. It is best known for its application as a distance function in unsupervised vector space models, such as in image retrieval. Equation for Jeffrey divergence distance metric is given by:

$$\delta(v_1, v_2) = \sum_{i=1}^{n} (P(C_i|v_1) log \frac{P(C_i|v_1)}{m} + P(C_i|v_2) log \frac{P(C_i|v_2)}{m})$$

where,

$$m = \frac{P(C_i|v_1) + P(Ci|v_2)}{2}$$

The best textural features are: energy (pixel uniformity), entropy (pixel complexity), contrast (local variation), correlation (linear patterns) and inertia. The local feature we extracted was ranked highest by Jeffrey divergence distance metric.

4.3 Support Vector Machine

Support vector machines (SVMs) are a set of related supervised learning methods that analyze data and recognize patterns, and used for classification. They are used for image classification by constructing an *N*-dimensional hyperplane, which optimally separates images into two categories. This mapping is performed by a set of mathematical functions, known as kernels.

We use SVM to classify our images into those indicating potential danger to cystic artery and others where cystic artery is safe.

4.4 Using All Image Attributes

We performed an experiment where we used all of the 23 features to let the SVM machine-learning algorithm decide which of the features are most relevant, rather than manually picking the features ourselves. We used dataset consisting of 900 images to train the classifier. The trained model was evaluated using a test set of 213 images containing 135 positive and 78 negative images.

The low accuracy of classification, might be an indicator that we have too many features and some of them are misleading the classifier.

Table 1. Summary of evaluation of 213 images with all features using SVM

Result Metric	Value
Correctly Classified Instances	135 (63.38 %)
Incorrectly Classified Instances	78 (36.61 %)
Kappa statistic	0
Mean Absolute Error	0.3662
Root mean squared error	0.6051
Total Number of Instances	213

4.5 Using Selected Attributes

We use the same dataset as before but with feature vector comprising of best features according to Jeffrey divergence distance metric and the local feature (average intensity) extracted by the image processing module of our method. Training and evaluation of this dataset using SVM boosts accuracy of classification to ~91%. This is a 26.7% increase in accuracy.

Table 2. Summary of evaluation of 213 images using SVM linear kernel

Result Metric	Value
Correctly Classified Instances	192 (90.14 %)
Incorrectly Classified Instances	21 (9.85)
Kappa statistic	0.7927
Mean Absolute Error	0.0986
Root mean squared error	0.314
Total Number of Instances	213

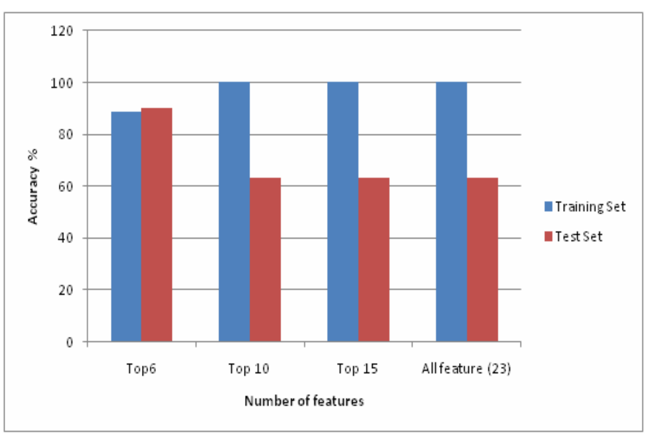


Fig. 9 Comparison for accuracy of image classification using different group of features as ranked by Jeffrey divergence distance metric

Observation of the image features show that the 'average pixel intensity' is a dominant feature in the feature vector. Our method performs well with linear kernel indicating the data is linearly separable.

5. DISCUSSION

Our system with the current approach of using a set of global image features and a objective-specific local feature, gives an accuracy of 90.14% for classifying images indicating a potential unsafe action from laparoscopic cholecystectomy video.

Due to the highly sensitive nature of medical data and the infeasibility of obtaining real videos with a large number of unsafe actions, we used a simulated laparoscopic cholecystectomy video for our experiments. Also the focus of this research was on detection of one particular unsafe action in laparoscopic cholecystectomy – accidental injury to cystic artery caused due to surgical instruments.

Our work could be further extended to detect various other unsafe actions that could potentially occur during the laparoscopic procedure. Other possible immediate enhancements to our system and its long-term applications could be:

5.1 Real time alerts

The foremost enhancement to this system would be to implement it in real time so that surgeons can get alerts as the operation takes place. Also our system would need to be integrated with existing operating room system to make it work in real time. As the image processing part can become time-consuming, corresponding execution can be moved to powerful servers. Images can be processed in parallel on different cores of the processor to boost the speed of execution.

5.2 Web Service

Our system can be enhanced to be used as a web service. The system in operating room would act as a web service client and the situation detection part used as a service. The client would stream the laparoscopy video and the service would send alerts if it detects a potentially unsafe action in the video. This can be further used in surgical training. Expert surgeons can monitor the surgical skills of their trainee surgeons remotely with this web service acting as intermediary. The web service can send a summary of the surgery performed by the trainee surgeon on the senior surgeon's smart phone. The summary would details such as number of potentially unsafe actions observed and time when those occurred.

5.3 Robot Assisted Surgery

Our system could act as an inexpensive alternative to costly detection devices used in robot-assisted laparoscopic cholecystectomy. Robot-assisted surgery is proven as a safe and feasible approach to laparoscopic cholecystectomy [25]. Our system can increase the level of situation awareness in a robotic-assisted or tele-operative surgery.

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