CLASSIFICATION OF UPPER AIRWAYS IMAGES FOR ENDOTRACHEAL INTUBATION VERIFICATION

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ABSTRACT

This paper addresses the problem of classification of upper airways images for endotracheal intubation verification in order to improve the safety of patients undergoing general anaesthesia. The proposed method is based on textural features utilized in a continuous probabilistic framework using parallel Gaussian mixture models (GMMs). The classification decision is made based on a maximum likelihood approach, which is insensitive to the angle at which the image was taken. Evaluation of the proposed approach is done using a dataset of 200 images that includes three classes of anatomical structures of the upper airways. The results show that the approach can be used to efficiently and reliably represent and classify medical images acquired during various procedures.

KEYWORDS

Artificial intelligence, intubation verification, Gaussian mixture models, textural features.

1. INTRODUCTION

Intubation is performed widely in hospitals and emergency medical units. During intubation, a flexible tube is used to secure passage of air to and from the lungs. The procedure is performed by manually opening the mouth, lifting the tongue using a device called laryngoscope in order to reveal the vocal cords, and inserting an endotracheal tube (ETT) through the vocal cords. The ETT should be positioned between 2 and 5 cm above the bifurcation of the trachea into the two primary bronchi ("carina").

The anatomy of the patient does not always allow easy insertion of the ETT and consequently it might be incorrectly positioned, usually either in the esophagus or in the right main bronchus. Both of these conditions can produce catastrophic results, as the patient might be deprived of oxygen. Unintentional esophageal intubation has been associated with high mortality rate [1, 2]. In cases of right lung intubation (also termed one-lung intubation (OLI)), only one lung is ventilated. Prolonged one lung ventilation might cause serious pulmonary complications such as collapse of the contralateral lung and hyperinflation of the ventilated lung, which might eventually result in hypoxia and pneumothorax, respectively, and has been associated with a significant increase in morbidity [3, 4] and Pneumonia [5]. Both esophageal and OLI may occur after the ETT was positioned correctly ("dislodgement") from many reasons, for example, due to neck flexion during general anesthesia [6, 7].

Confirmation of correct tube positioning is a challenging task that requires high skills and the use of secondary objective devices. Numerous studies, which investigated endotracheal misplacement rates in hospital and pre-hospital settings, reported rates between 0% and 25%, depending among others, on study design [1, 2, 5, 8-13].

There are various methods and techniques for endotracheal intubation confirmation. The most common technique is auscultation to lung sounds using a stethoscope. This technique requires high attention, and its reliability has been questioned in many studies [14-20]. The use of exhaled carbon dioxide detection (CO_2) measurements (termed end-tidal CO_2 ($ETCO_2$)), has become the gold standard-de-facto for confirming correct tube positioning. However, the method has been found to be unreliable in many emergencies [21-25]. In addition, the method can not be used to detect OLI incidents as in such cases the capnogram is generally typical in shape and shows normal $ETCO_2$ values [22, 25]. Other techniques have been proposed (e.g., [26-30]), but none of them has been proven effective. Therefore, attempts to find the ultimate technique for correct tube position confirmation have been continued.

In this paper, we further develop a previously-proposed system [31, 32] for endotracheal intubation confirmation. The system is based on identification of specific anatomical landmarks as indicators of correct or incorrect tube positioning, based on a continuous probabilistic approach using textural features.

2. MATERIAL AND METHODS

2.1 The System

Intubation is usually performed using an intubating stylet, used to control and guide the ETT. We designed and assembled a designated video-stylet. The tip of the stylet comprises a miniature complementary metal oxide silicon (CMOS) sensor. The inner part of the stylet contains wires to transfer the image and a narrow lumen to spray water or air in order to clear blood and secretions away from the camera sensor. The image sensor is connected to a processor with an integrated image acquisition component. During intubation, this rigid stylet is inserted into a standard ETT with its camera at the tip. Video signals are continuously acquired and processed by the confirmation algorithm implemented on the processor.

2.2 Pre-Processing and Textural Features

The classification system is a supervised one and comprises three main steps. The first step is conversion of the acquired image from a color image (RGB) to a grey scale image, which is followed by feature extraction. Various features have been utilized in medical image applications, including squared grey-level difference [33], cross correlation [33] and localized intensity features [34]. In this work, textural features [35, 36] were used. Textural features contain important information about the structural arrangement of surfaces and their relationship to the surrounding environment. In particular, features based on grey level co-occurrence matrices (GLCM) were utilized. These features are based on the assumption that textural information on an image is contained in the overall or "average" spatial relationship, which the grey tones in the image have to one another [37]. More specifically, it is assumed that this textural information is adequately specified by a set of grey tone spatial dependence matrices which are computed for various angular relationships and distances between neighbouring resolution cell pairs on the image. The advantages of these features is that they are robust to small differences in the imaging directions and scaling. This property is of great importance in many medical imaging applications.

2.3 The Gaussian Mixture Model (GMM) Probabilistic Framework

In order to classify the images, a probabilistic framework is utilized, in which the images are represented in the feature space using Gaussian mixture models (GMMs). GMM based classification methods have been largely applied to speech recognition [38], and recently to some medical image categorization applications [31, 34]. Mixture models, in particular GMM, form a common technique for probability density estimation. This is justified by the fact that any density can be estimated, in a required degree of approximation, using finite Gaussian mixture [39]. Their mathematical properties, as well as their flexibility and the availability of efficient estimation algorithms, make them attractive for classification problems. The most popular algorithm for GMM parameters estimation is the expectation-maximization (EM) [39]. This algorithm allows iterative optimization of the mixture parameters, under monotonic likelihood requirements, and has a relatively simple implementation. In this study, the probability density functions (pdf) of the images were represented, in the feature space, by three classes, where each class was modeled by a combination of four GMMs. Each GMM, representing a random process, x, is defined as a weighted sum of K Gaussian components, as follows:

$$f_K(\mathbf{x}) = \sum_{k=1}^{K} \pi_k \phi_{\theta_k}(\mathbf{x}), \tag{1}$$

where π_k represents the mixing weight such that $\sum_{k=1}^{K} \pi_k = 1, \pi_j \geq 0 \forall j$ and $\phi(\mathbf{x}; \theta_j)$ represents the jth d-dimensional Gaussian mixture component given by:

$$\phi(\mathbf{x}; \theta_j) = \left(2\pi\right)^{-d/2} \left|\mathbf{S}_j\right|^{-1/2}$$
$$\exp\left[-0.5(\mathbf{x} - \mathbf{m}_j)^T \mathbf{S}_j^{-1}(\mathbf{x} - \mathbf{m}_j)\right], \tag{2}$$

which is parameterized on the mean $\mathbf{m}_j$ and the covariance matrix $\mathbf{S}_j$, collectively denoted by the parameter vector θ_j.
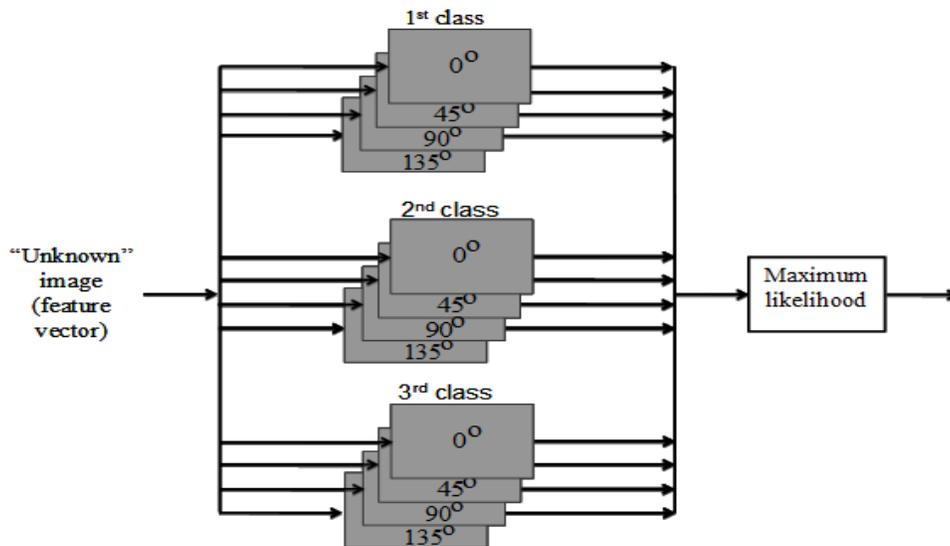
Figure 1. The parallel model approach

2.4 The Parallel GMMs Scheme

During endotracheal intubation, a common procedure in operating rooms, the tube is inserted into the patient's mouth in an horizontal direction, i.e., an angle of 0°, where the head of the tube turns away from the patient. While inserting the tube into the trachea, the medical professional rotates the tube counter clockwise until it reaches a vertical direction (90°). Therefore, the acquired images might be rotated with respect to the images that were used to train the models and therefore pre-alignment of the images prior to their classification is required. Traditionally, two approaches have been used to overcome this common problem: (a) employ an image registration technique prior to classification [40], (b) utilize features which are insensitive to the imaging angle [37]. Common to these approaches is their computational complexity, which is a major drawback when real-time classification is required. An alternative model based approach is proposed, according to which several models are used to represent each class of images, where each "sub-model" represents images taken at a specific range of angles, i.e., a GMM for angles around 0°, a GMM for angles around 45°, etc. During the training phase, a model is estimated using the images of each and every class, resulting in a total of 12 models (4 models for each one of the classes). During the testing phase, an "unknown" image is classified according to a generalized maximum likelihood rule, i.e., the selected model is the one which one of its sub-models provides the maximum likelihood (ML). The classification decision rule is therefore given by:

$$m = \arg\left\{ \max_{l=1,2; \ s=1,2,\ldots,S} f(O \mid \lambda_{ls}) \right\}, \qquad (3)$$

where λ_{ls} represents the s th sub-model of the l th group. Figure 1 presents the parallel models scheme.

3. RESULTS

In order to evaluate system performance, we used a database of 200 images recorded from the upper airways of 10 patients where the images were taken at different angles and directions. The details of this database appear elsewhere [41]. The dataset used in this work includes 200 randomly-chosen images from the available database, that were visually inspected by a medical expert and classified into one of the following categories: upper-trachea, carina and esophagus. Each of these classes was further divided into four sub-groups representing 4 quantized imaging angles- 0°, 45°, 90° and 135°. Evaluation of the proposed approach was performed using a leave-one-out validation method: in each iteration, 199 of the images were used to train the models and the remaining image was used to test system performance. This process was repeated 200 times, such that each image participated once in the testing phase.

The classification results are summarized in Table 1, where the rows represent the predicted (identified) classes and the columns represent the actual classes. In this case, the order of each one of the GMMs was set to 8. The system achieved an overall classification rate of 92.0%.

Table 1. Confusion matrix of the three classes

Identified	True		
	Upper tracheal	Carina	Esophagus
Upper tracheal	92%	3%	5%
Carina	5%	94%	6%
Esophagus	3%	3%	89%

4. CONCLUSIONS

A method for classification of upper airways images based on a probabilistic framework using textural features was presented. A parallel scheme utilizing GMMs is used to represent images taken at different angles. While the training phase, which is usually a one-time phase, requires a tedious manual segmentation of the dataset according to the different sub-groups (for each range of imaging angles), the testing phase is based on a simple ML decision rule among the models of each class. Therefore, the proposed scheme is simple and computationally efficient. It should be noted however that further work is needed in order to evaluate the performance of the proposed approach and to compare it with other methods proposed in the literature.

All of the algorithms used in this work were implemented in Matlab R2016a 64bit. Using a conventional PC equipped with Dual Intel Xeon 3.4 GHz with a 4 GBytes of RAM, feature extraction requires about 1.5 second for each image and the parallel ML based decision rule requires approximately 1 second for each image. Efforts are currently being invested to collect a larger database in order to allow a more thorough investigation of the proposed approach.

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