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Chapter Mark Addition Based on Anomalousness for Surgery Videos Using CHLAC Features

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Abstract

We propose a chapter mark addition method for surgery video application that adopts cubic higher-order local auto-correlation (CHLAC) features. In our method, normal motions, which frequently occur in a scene, are statistically learnt by using CHLAC in combination with the subspace method. An anomalous motion exists far from the subspace of the frequently-observed motions and such motion is detected based on the deviation from the subspace, and a chapter mark is placed just before the position of the detected anomalous motion. We conducted preliminary experiments using surgery video data to confirm effectiveness of the proposed method. The results show that the proposed method can detect the motions not frequently-observed in a surgery operation and the chapters are effectively constructed.

Keywords: *Chapter Mark; Anomalousness Detection; Cubic Higher-Order Local Auto-Correlation (CHLAC); Surgery Video; Surgical Safety Support System*

1. Introduction

Many of the hospitals record surgery operations on video. These surgery videos have so far been used mainly for teaching new techniques in operations for younger doctors. On the other hand, in surgical safety support systems, which have recently been developed, the recorded videos are used for finding potential risks that may induce medical accidents (unexpected incidents) in the surgical operation. Those systems recording views solely of the surgery field are commonly found [1]. A system recently developed has not only multiple cameras but multiple views in the surgery room different angles in addition to surgery views [2]. Surgical operations will be carried out more safely if those risks are removed. Multiple cameras in the system (shown in Figure 1) record many objects in the surgery room from various views: such as a surgery field, panoramic view of the surgery room, and an anesthetist and surgical tools. The content of the video will be carefully examined to find risks. However, if the duration of the video gets longer, it becomes harder for them to check all the critical events in the video from the first place. For example, it takes over ten hours to complete a surgery for brain tumor, which is recorded by with ten cameras. Use of a chapter marking that is placed just before a crucial time point in the video will reduce the reviewer's workload: they can carry out their task efficiently starting from the chapter mark.

In general, troubles in the operation and intervals of the stages in the surgery are considered as crucial points. In this paper we propose a chapter marking method based on anomalous motion detection. This is because motions that are hardly seen are considered the results that the surgeons have not anticipated. And because it is assumed that there are motions hardly seen such as movement of bed in the intervals of the stages in the surgery.

In our method, normal motions, which frequently occur, are learnt statistically by using CHLAC feature in combination with the subspace method [3, 4, 5]. Therefore, an anomalous motion can be detected based on the deviation of a motion feature from the learnt subspace for the motions frequently-observed, and chapter is marked just before the detected anomalous motion. A statistical approach in the proposed method does not require provision of learning data that tell what is crucial. Thus, the system we propose with the statistical approach will prevent the reviewer from missing the less-frequently-observed motions.

We describe the detail of the method in section 2, report on the result of the experiments in section 3, and make a summary in section 4.

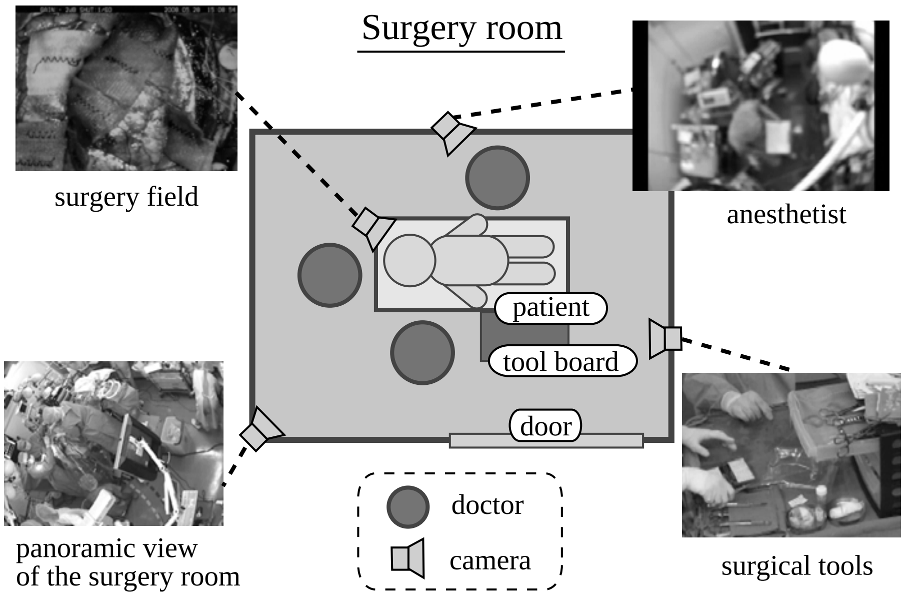

Figure 1. Many cameras in the surgery room

2. Proposed method

We can see a variety of motion patterns in a recorded surgery. The method we propose classifies those motions into two groups, *normal* and *anomalous* motions, by the following definition. A normal motion is frequently observed, whereas anomalous is *not* frequently observed. We assume that anomalous motions are not anticipated by the surgeons and thus a risk can be found in those motions. Our method shows possible candidates of crucial points to the reviewer by chapter marks.

2.1. Scene analysis technique for proposed method

The method we propose is based on the scene analysis technique that determines whether a motion in a surgery video is normal or anomalous, according to statistical criterion. Walking on a street, for example, would not be a motion that draws much attention whilst running would. However, motions of walking on a track will draw more attention than running in a situation where you see motions of running quite often. Thus, what draws your attention depends on the scene. The proposed method does not require the user to prepare a reference of an anomalous motion since it statistically learns the criteria to decide what sort of motions we need to pay attention through the scenes over the video.

2.2. Cubic higher local auto-correlation (CHLAC)

We use the CHLAC feature, which is an advanced HLAC feature [6, 7] by considering correlations in time line, to deal with video data. Our method extracts CHLAC motion features [5] from the video data at the first stage for statistical learning. The CHLAC feature is a 251-dimensional vector characterizing both of shapes and motions of the objects in the video. CHLAC feature has following three advantages: (a) unnecessary to extract a block of image data prior to the process where actual detection of the motion takes place; (b) no prototype model with which targeted objects is to be compared; (c) a little amount of calculation time. The proposed method using CHLAC feature allows the user to detect anomalous motions in the surgery video without running high-performance server.

Performance at high degree of precision in gait recognition using CHLAC feature has been reported in [5]. CHLAC features have been applied to a wide range of fields [8, 9, 10].

2.3. Anomalousness detection

We use a linear subspace method to detect anomalous motions in given video data [4]. CHLAC features extracted from normal motions are distributed in a certain region in the (251-dimensional) feature space. The distribution of the features can be represented as a subspace.

We use (*Principal Component Analysis: PCA*) to find the basis vectors (eigenvectors) for constructing the subspace S_N of normal motions that is frequently observed. The eigenvectors $U = [u_1, \cdots, u_{251}]$, $u_i \in R^{251} (i = 1, \cdots, 251)$ are calculated by solving the following eigenvalue problem:

$$RU = U\Lambda \tag{1}$$

where $\Lambda = diag(\lambda_1, \cdots, \lambda_{251})$ is the eigenvalue matrix. If λ_i are in descending order, the contribution rates $\eta_k (0 \le \eta_k \le 1)$ are represented as

$$\eta_k = \frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{251} \lambda_i} \tag{2}$$

We take the first k eigenvectors for S_N, where k is the smallest number under $\eta_k \ge \tau$ (say, $\tau = 0.99$). The projection operator onto S_N is given by $P = U_k U_k^{'}$, where $U_k = [u_1, \cdots, u_k]$. Then, the projection onto orthogonal-complement subspace to S_N is given by $P_\perp = I_{251} - P$. The distance $d_\perp$ between a given feature vector x and the subspace of normal motion S_N is formulated as

$$\begin{aligned} d_{\perp}^{2} &= \left\| P \perp x \right\|^{2} \\ &= x^{'}\left(I_{251} - U_{k}U_{k}^{'}\right)x \end{aligned} \tag{3}$$

In this paper, we call $d_{\perp}$ as the anomalous motion value as shown in Figure 2. A chapter mark is inserted into video data associated with anomalous motion values.

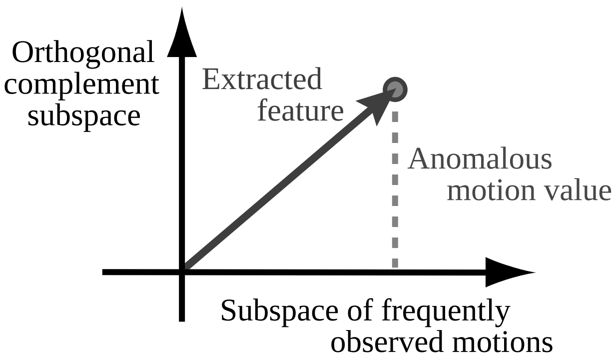

Figure 2. Anomalous motion value

2.4. Developed system for proposed method

The whole processes in the proposed method falls into two phases: the learning phase and the detecting phase as shown in Figure 3. CHLAC features are extracted from the video data in both phases. In the learning phase, we extract CHLAC features from the inter-frame differentials of the grey-scale learning video data. Applying PCA to the CHLAC features, we obtain the subspace of the frequently-observed motions in the feature space.

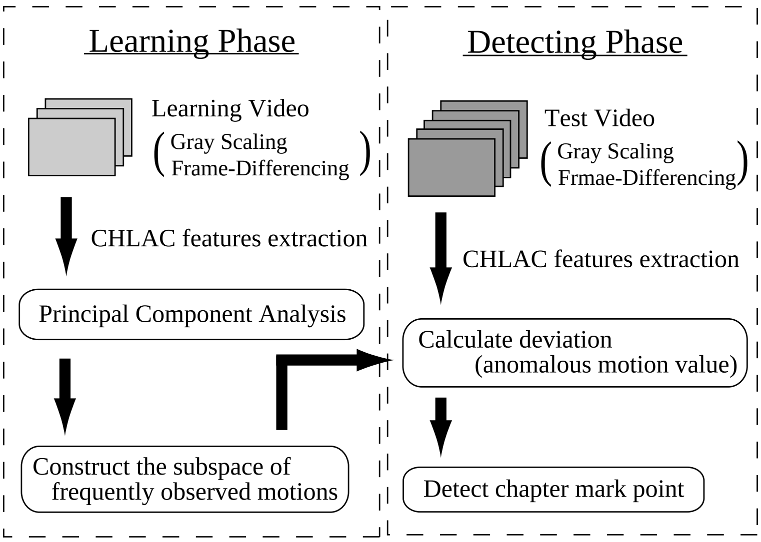

Figure 3. Outline of the proposed method

In the detecting phase, CHLAC features are also extracted from inter-frame differentials of the gray-scale test video data. We calculate an anomalous motion value as a distance from an extracted feature to the subspace of frequently-observed motions. We have now the set of anomalous motion values exceeding the threshold A_{th} defined above.

$$A_{th} = \mu_d + \alpha\sigma_d \tag{4}$$

where μ_d and σ_d are the average and the standard deviation of the anomalous motion values, respectively, and α is a coefficient given by the user. The developed system inserts a chapter mark just before the motion whose corresponding anomalous motion value exceeds the threshold. Note that a chapter mark precedes only the first point of the motions if their anomalous motion values exceed consecutively.

3. Experiment

We conducted preliminary experiments using two cameras to take surgery video data to confirm effectiveness of the proposed method. The videos data used for the experiments were taken panoramic view of the surgery room (video A) and view of anesthetist (video B) as shown in Figures 4(a) and 4(b). The surgery videos were split into two parts as shown in Figure 5; the first half of surgery is for the learning video, the second half is for the test video. The size of video is 360 x 240 pixels and frame rate is 30fps. We take 0.999 and 2 as the value of the contribution rate μ_k in formula (2) and the value of the coefficient α in formula (4) respectively for both video A and video B. The subspace for video A and video B is generated independently by the system. The chapter mark points for video A and video B are obtained using the subspace of frequently-observed on video A and video B respectively.

(a) panoramic view of the surgery room (b) view of anesthetist

Figure 4. Angle of the surgery video

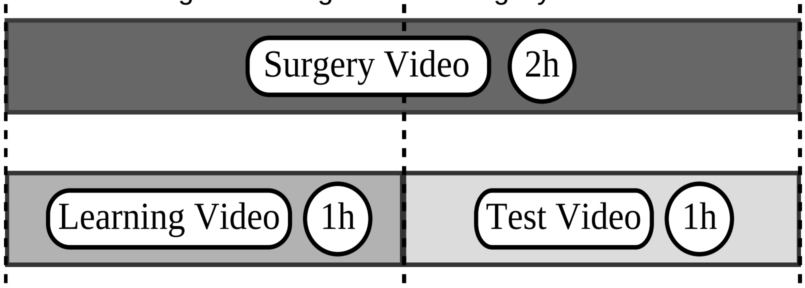

Figure 5. Set up for learning and test video

3.1. Detected anomalous motion values

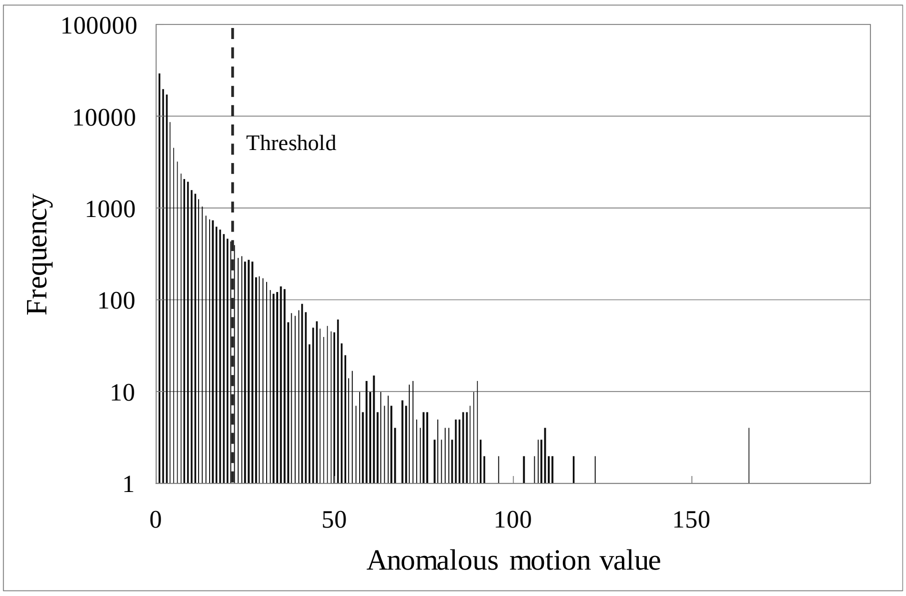

Figure 6. Histogram for detected anomalous motion values (video A)

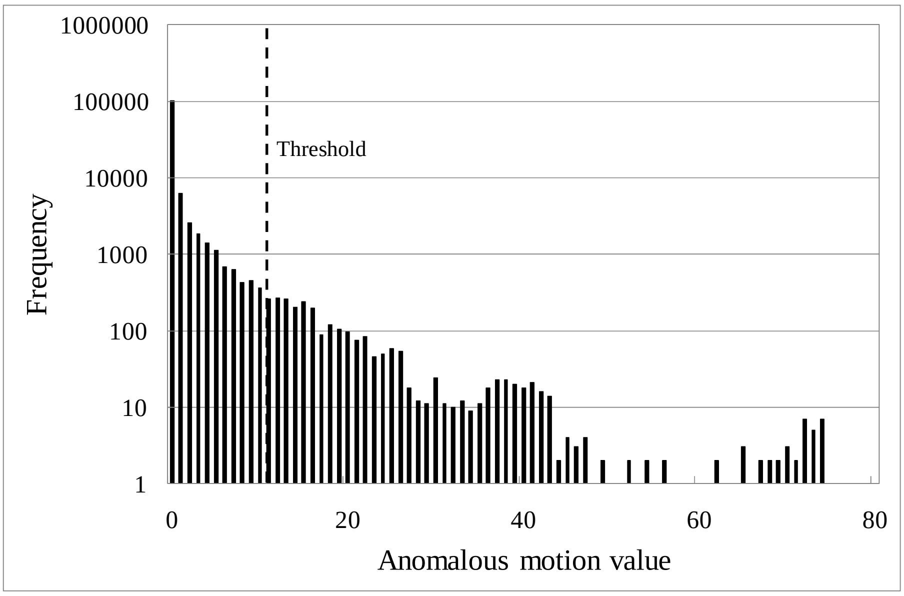

Figure 8. Histogram for detected anomalous motion values (video B)

At the end of the learning phase, the number of base vectors generating the subspace for normal motions for video A and video B is 25 and 87 respectively. This implies the features for normal motions are distributed in a limited space in the whole feature space of 251-dimension. The determined threshold is about 25 for video A and about 11 for video B.

Next, we calculate the anomalous motion value in the detecting phase. The test video data used in the detecting phase was not used in the learning phase. Figures 6 and 7 show the histograms of anomalous motion values on log scale calculated for video A and video B respectively. As the result of the experiments almost all the motions in the surgery videos we used are considered normal.

Applying the threshold value (obtained) chapter marks are added to the video. Figures 8 and 9 show the chapter mark points added to video A and video B respectively. The horizontal axis on the both charts shows the elapsed time over the video. The thicker stripes are the denser the chapter mark points are added. There are 77 and 61 of chapter mark points added to video A and B respectively.

Many chapter marks are inserted in the first half of the video A such as setting up the surgical equipment. This is because preparation for the surgery is seen in the first half of the video A. We have confirmed that not-frequently-observed motions are found between the stages of the whole process of the surgery.

However, the number 77 and 61 of chapter mark points detected look slightly more to see in just an hour. The reason for such large numbers is that the current system counts up every single chapter mark point no matter how short their intervals are. This problem can be solved by choosing a single chapter mark representing others found in a short period.

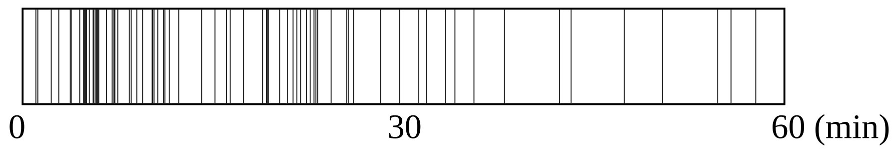

Figure 8. Added chapter mark points (video A)

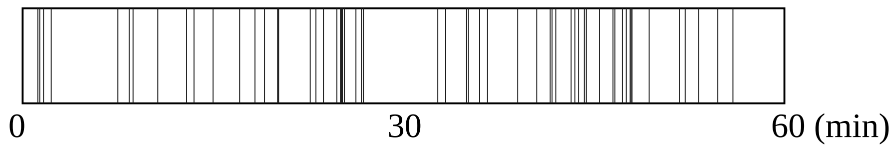

Figure 9. Added chapter mark points (video B)

3.2. Detected anomalous motions

The followings are examples of anomalous motions found with the chapter mark points in the detecting phase. Figures 14 and 15 show the graph of the anomalous motion values taken from video A and video B respectively along with the same time period. The frame number is shown in the horizontal axis and anomalous motion values in the vertical axis. In the scene marked with (i) on video A, a person carried something in her hand with stretched arms in front as shown in Figure 10. In the scene marked with (ii) on video A, two people on image moved around a wagon. One of them went to third person and bent forward at the foot of the person to pick up something as shown in Figure 11. There is no higher anomalous motion values observed on video B in the same periods of (i) and (ii) while higher (than the threshold) anomalous motion values are seen. This is simply because video A and video B takes views from totally different angles and no overlaps in still objects and scenery.

Figure 10. Detected motion (video A, (i))

Figure 11. Detected motion (video A, (ii))

Figure 12. Detected motion (video B, (i))

Figure 13. Detected motion (video B, (ii))

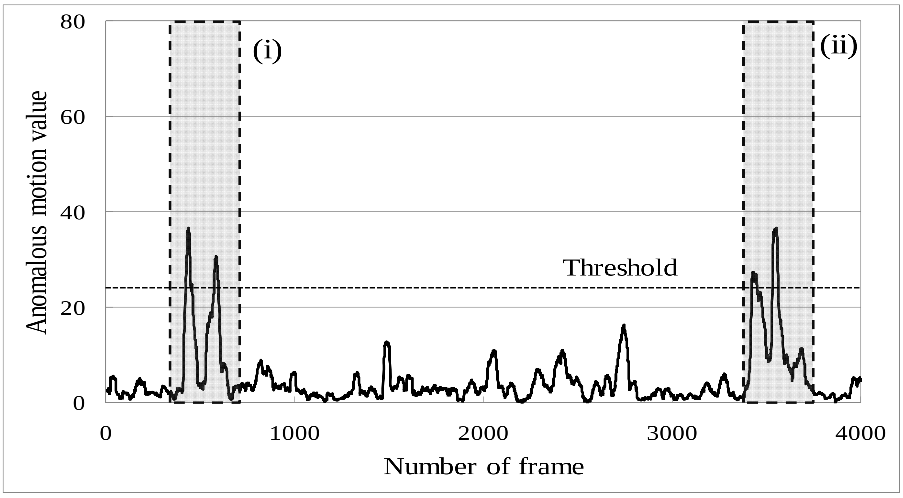

Figure 14. Anomalous motion values (video A, (i), (ii))

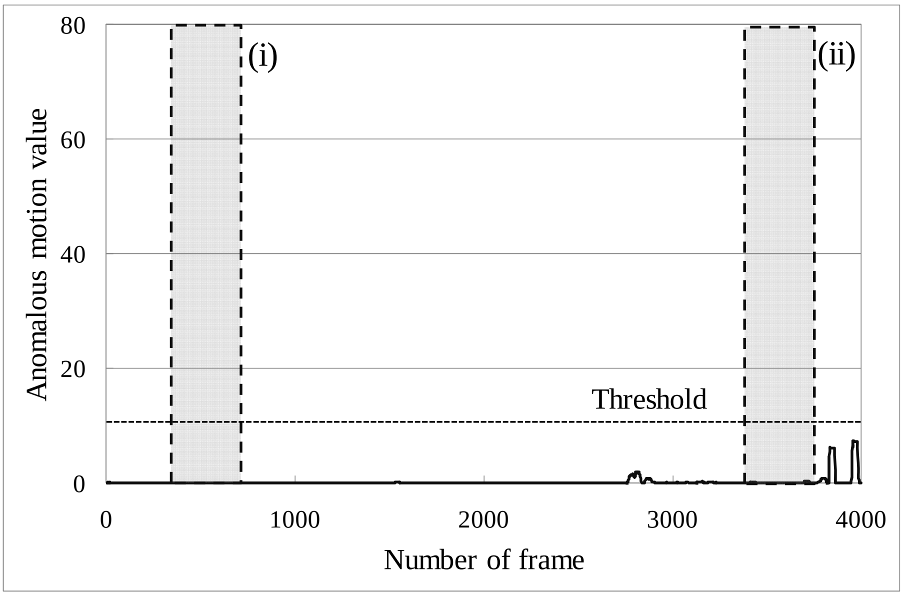

Figure 15. Anomalous motion values (video B, (i), (ii))

Figures 20 and 21 show the graph of the anomalous motion values taken from video A and video B respectively along with the same time period. In the scene marked with (iii) on video B, an anesthetist carries a box-like object. The anesthetist passed it on to another person in a cut as shown in Figure 16. A series of these motions recorded on video B are detected anomalous but not recorded on video A surely because two videos are taken from different angles. However, further investigations have revealed that the box-like object and similar behaviors have found on the video A (Figure 17) just before the time high anomalous motion values are found in period (iii) (Figure 21) and also higher (than the threshold value) anomalous motion values are found on video A in period (iii) (Figure 20). Which means, there is some correlation in anomalous motions observed on video A and video B at around the time.

Figure 16. Detected motion (video B, (iii))

Figure 17. Detected motion (video A, (iii))

We have looked into the scenes showing other high anomalous points (exceeding the threshold) on video A and video B. In the scenes in the period of (iv) on video A, a surgeon held an object whose shape has hardly been seen in the surgery other than in the period and walked around in the room. In the scene marked with (v) on video A, a surgeon carried an object in not-frequently-observed shape, walked in arc and turned round at a corner of the screen as shown in Figure 18. We have seldom seen such a motion he made in the surgery other than the time period (v). In the scene marked with (vi) on video B, A light has started moved from right to left at the bottom of screen as shown in Figure 19.

Figure 18. Detected motion (video A, (v))

Figure 19. Detected motion (video B, (vi))

These results show that the proposed method can detect not-frequently-observed motions in a surgery operation. Conversely, it does not detect normal or frequently-observed motions such as walking.

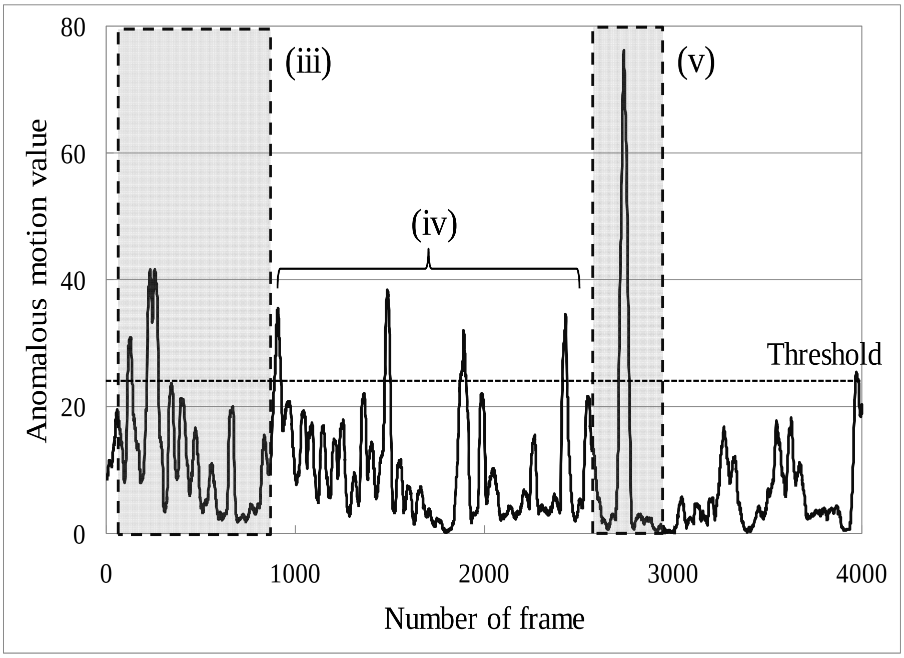

Figure 20. Anomalous motion values (video A (iii)-(v))

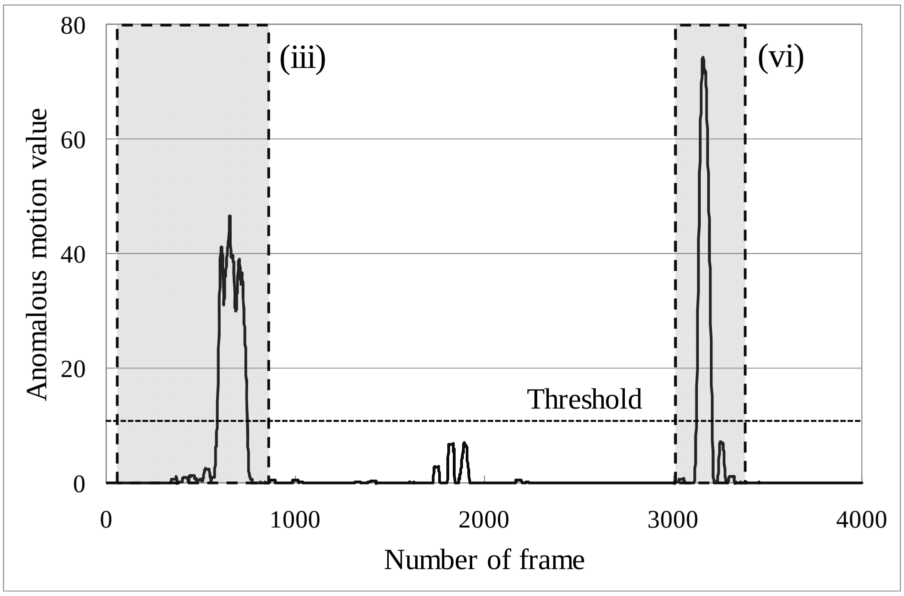

Figure 21. Anomalous motion values (video B (iii),(vi))

4. Conclusion

We have proposed a chapter mark addition method using CHLAC features for surgery video applications and have successfully demonstrated in the preliminary experiment described above that the method can detect the motions not frequently-observed in contrast with those frequently observed. We are going to apply the proposed method to other video data taken from various angles and attempt to validate our approach.

We have confirmed that there are correlations in anomalous motion values between two videos under some conditions. We are going to develop a new method which finds points for placing chapter marks making use of the correlation among multiple videos.

It will be possible to cognize crucial events in a surgery operation from information other than motion images. Heart beats and voice of the surgeons and the nurses in the operation room, sensors in the equipment for the surgery, and the vital information taken from the patient could be indications for crucial events. Development of a method to combine our approach described in this paper with other information as listed above will be our future work.

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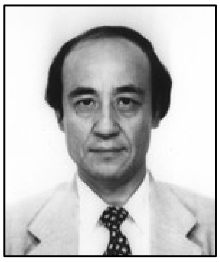

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