Noise Filtering of New Motion Capture Markers Using Modified K-means

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Abstract
In this report a detailed description of a new set of multicolor Illuminated Contour-Based Markers, to be used for optical motion capture and a modified K-means algorithm, that can be used for filtering out noise in motion capture data are presented. The new markers provide solutions to central problems with current standard spherical flashing LED based markers. The modified K-means algorithm that can be used for removing noise in optical motion capture data, is guided by constraints on the compactness and number of data points per cluster. Experiments on the presented algorithm and findings in literature indicate that this noise removing algorithm outperforms standard filtering algorithms such as Mean and Median because it is capable of completely removing noise with both Spike and Gaussian characteristics. The cleaned motion data can be used for accurate reconstruction of captured movements, which in turn can be compared to ideal models such that ways of improving physical performance can be identified.

Keywords: multimedia data mining methods and algorithms, knowledge extraction from video data, intelligent systems for interactive entertainment, pre-processing and representation of multimedia data.

1 Introduction

This report is a part of a body of research that aims to develop an automated intelligent personal assistant, which can facilitate classification of complex movements and assist in goal-related movement enhancement endeavors. The overall research is divided into two major phases. The first of these two phases aim to develop a personal assistant that will support athletes with improving their physical performance. To construct this personal assistant a new cost-effective motion capture system, which overcomes the limitations in existing systems and techniques that support intelligent motion capture recognition, must be developed. Phase two of the overall research focus on developing a physical prototype of the Multipresence system suggested by the author in [1, 2]. This Multipresence system will be constructed in a way that allows the personal assistant to control it using intelligent motion capture recognition techniques.

The report will focus on the first phase of the overall research and to complete this phase a number of areas must be investigated. These areas include:

1. Camera and volume calibration
2. Construction of a new marker system, which does not have the limitations associated with Classical spherical flashing LED based markers.
3. Motion data capturing and pre-processing
4. Noise filtering
5. Marker centre point estimation
6. 2D to 3D conversion of marker coordinates
7. Construction, fitting and temporal updating of skeleton
8. Development of an intelligent motion recognition system

A brief overview of general motion capture techniques is provided first, with the focus being on marker based optical motion capture. Proposed solutions to point two, three and four from the above list, will then be explained in detail. As a response to point two, a new set of multicolor Illuminated Contour-Based Markers [3] is presented. A dimensionality reduction procedure, which simplifies the captured motion data, such that further processing becomes less complex, is then proposed as a solution to step three. Finally a modified K-means algorithm [4], which can be used for inter-frame noise reduction in images with optical motion capture data, is presented as a solution to step four.

1.1 Motion Capture

Motion capture systems are tools for accurately capturing complex real world movements. Typically these captured movements are used in the movie, animation and games industries where high quality representations of movements are required in order to support suspension of disbelief. More recently motion capture has also been used as a tool to aid in human motion analysis. Results from this kind of analysis can be used to identify ambiguities with the physical performance of athletes, or to assist in diagnosing people with illnesses that affect their movement [5]. Some research also indicate that motion capture can be used for controlling humanoid robots [6].

There is a range of different motion capture technologies available. These technologies span from optical, magnetic, mechanical, structured light, radio frequency and acoustic systems to wearable resistive strips and inertial sensing systems, or combinations of the above [7]. All these technologies have varying degrees of drawbacks. Optical, acoustic and structured light systems suffer from occlusion problems, magnetic and radio frequency trackers suffer from noise and echo problems, mechanical systems have a non-user friendly interface that undermines emersion, inertial sensors suffer from bias and drift errors, while resistive strips must be built into a body suit, which makes them difficult to calibrate for different users [7, 8, 9, 10]. Another drawback with many of the abovementioned systems is also that they are high-end and therefore quite expensive, which makes it hard for many individuals and small companies to acquire the necessary technology [5, 11].

The optical approach to motion capture has been selected for this research. The reason for this is that the intension is to capture movements in controlled environments and the occlusion problems usually associated with the optical approach therefore will be limited. Other reasons for choosing this approach are that this class of systems has proved to support accurate capturing, have only limited noise problems, do not suffer from echo problems and there is cost effective ways to construct these systems. Optical systems can also easily be designed in a way that does not limit the user's freedom of movement. Another important factor for selecting the optical approach is that capturing can be performed in real-time.

1.2 Optical Motion Capture

What systems that use the optical approach to motion capture have in common is that they use cameras as sensors. In general, this class of systems can be divided into two sub categories. These two categories are referred to as marker-less and marker-based approaches to optical motion capture. This research will focus on marker-based approaches, because currently only these can track complex and detailed motions effectively enough to support real-time processing [11].

1.3 Marker-based Tracking

In early motion capture systems, most contour points of the tracked subject were suppressed in order to achieve real-time processing. The points that where not suppressed where referred to as markers [12]. Today, in order to qualify as a marker, an object must contain two pieces of information: what the object is in relation to the current process and where this object is located [13]. Currently there are two main types of markers: Passive and Active. Both these marker types will be described briefly below.

Passive Markers

The characteristics of passive marker systems are that the markers must be manually identified. A Classical passive system is constructed of spheres that are 2.5 cm in diameter and are covered with a highly reflective material that often is over two thousand times brighter than a normal white surface [14]. The material covering the marker reflects light (in many cases infrared) projected from light sources positioned around the lens of each camera. These reflections give the markers a distinctive color compared to the rest of the image and therefore support marker extraction. A Classical passive marker is shown in Figure 1.

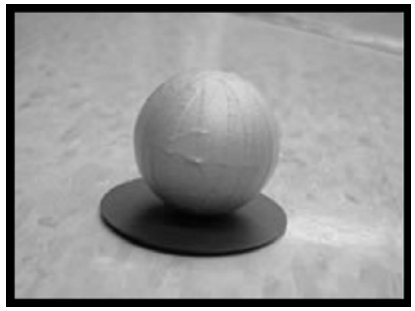

Fig. 1. A classical spherical marker [15].

The main drawback with passive systems is that either a trained human operator or a specific start-up pose of the performer is required for identifying the makers. A second drawback is that even if all markers have been correctly identified initially, their ID will be lost after an occlusion. As a result of this, it seems like a new unknown marker emerge when a occluded marker reappears [16]. These occlusions can in addition to contributing to the generation of false markers, create holes in incoming data streams [17, 18, 19, 20].

Active Markers

What active marker systems have in common, is that they express sufficient information to support automatic marker identification. There are several variations of active marker systems such as the square markers presented by [21] and the retro reflective mesh based markers presented by [6], but the most commonly used active marker is constructed of sets of spherical flashing light emitting diodes (LED's). Each of the LED's in these commonly used markers are wired to an external computer, which provides them with distinctive flash sequences that allows each marker to communicate their ID automatically. The computer also ensures that the markers "flash" in synchronization with the digital shutters of the capturing cameras [16, 22, 23].

A drawback with Classical spherical LED based active markers is that more than one image must be analyzed in order to identify each marker, which makes the processing time longer than if methods that support more direct identification was used. One such direct method is to use static colors to express ID's rather than flash sequences. The problem here is that colors tend to change when they are exposed to different lightning [24]. Knowledge about the motion of tracked markers has therefore been used to support the color cue, but there are difficulties associated with this approach as well. This because of severe discontinuities in human motion and delay in frame processing [25, 26]. A second problem with the flashing LED type active markers is that the wires that run from markers to the computer restrict the user's freedom of movement [22, 23]. The result is that captured movement in some situations can appear un-natural and that the tracking process may be too cumbersome for use in some applications, especially in medical applications where users may have some kind of movement disability. Both the initial and the latter are highly undesirable. The initial because a tracking system that in any way makes the movement appear un-natural undermines one of the central aims of motion capture, which is to capture realistic movement (this is also the drawback with the constraints posed on the users of the markers presented by [24]). The latter is undesirable because a system design that makes the tracking process cumbersome prevents a range of people from benefiting from the technology. A third drawback with using flashing spherical LED type markers is as with spherical passive markers, that they easily create holes in incoming data streams as results of occlusions.

1.4 Proposed Solution to Drawbacks with Classical Markers

To solve and/or reduce the abovementioned drawbacks with current marker systems, the researcher propose the set of active multicolor Illuminated Segment-Based Markers described by the author in [3]. These markers express their identity using different pairs of long intersecting line segments with internally produced static colors. These colors are illuminated into the environment and are therefore more robust towards changes in external lighting than colors produced by reflected light. This way of solving the identification problem gives the markers an edge over Classical spherical LED based active markers. This because static color cues allow markers to be identified within one single image, rather than trough a sequence of images and therefore allows for a reduction of processing time. The use of static colors also eliminates the need for wiring markers to a complex external computer, removing the restrictions usually posed on user movement by Classical flashing LED based marker systems. Another central strength of the Illuminated Segment-Based Markers is that they support more robust estimation of missing data, than traditional markers. This because the proposed markers allow for both intra-frame interpolation of missing data and inter-frame estimation of occluded intermediate sections of line segments. This strength is highlighted by the fact that the Illuminated Segment-Based Markers are designed to be larger than traditional markers and therefore have a greater chance of retaining enough data to estimate missing marker positions inter-frame than Classical markers. This in turn results in a reduced chance of having to assume intra-frame linearity in the case of occlusions.

Design specifics and results from experiments on the Illuminated Segment-Based Markers are described in greater length in Section two and three.

1.5 Characteristics of Optical Motion Capture Data

High dimensionality and noise is naturally embedded in time series data and makes it a challenging task to process sequences of motion data [27]. To solve this problem in an effective way, initial processing should involve a dimensionality reduction procedure, which simplifies the data. Such reductions are typically performed by flattening regions where data only varies gradually, or not at all [28, 29, 30]. Noise can in general be referred to as any entity that is uninteresting for achieving the main goal of the computation [31]. These uninteresting entities can be introduced to optical motion data as a result of the constant fluctuation of light, interference of background objects, external artifacts that corrupts the analogue-to-digital conversion process, accuracy limitations of sensors or transmission errors [7, 8, 31]. It is important to notice that some types of noise may be invisible initially, but can be accumulated over time, resulting in increased data complexity and/or data being incorrectly classified [7, 28, 32, 33]. To avoid this, one should aim to exclude as much noise from the data as possible before main processing is initiated. To remove noise most effectively, one should investigate where it originates from and analyze its characteristics so that knowledge obtained from this process, can be used for designing an suitable filtering algorithm for the noise at hand.

2 Experimental Design

In this Section, we will describe the strengths of the Illuminated Contour-Based Marker System and explain how these are assembled. Then a description of the nature of the captured data and an outline of how data is captured and pre-processed is provided. At the end of the Section, we present a detailed design overview of the proposed Modified K-means algorithm, which is used for removing inter-frame noise in optical motion capture data.

2.1 The Illuminated Contour-Based Marker System

The Illuminated Contour-Based Markers are constructed of intersecting pairs of 3mm thick battery powered, flexible glow wires of different colors. These glow wires are made of copper wires with phosphorus powder coatings and are protected by insulating plastic in different colors. The wires operate on alternating currents using a small battery driven inverter. When a current is transmitted trough a wire the phosphorus produce an illuminating electroluminescent glow [34]. The appearance of this glow depends on the color of the insulating plastic layer covering the wires. Ten different types of glow wire are available on the market to day. A glow wire can be observed in Figure 2. The glow wires are cut into appropriate lengths, and pairs of wires with different colors are assembled into markers in such a way that the two wires intersect and each marker is identifiable by its distinctive color combination. The intersection between wires is regarded as being the marker midpoint. Sets of Illuminated Contour-Based Markers are shown in Figure 3.

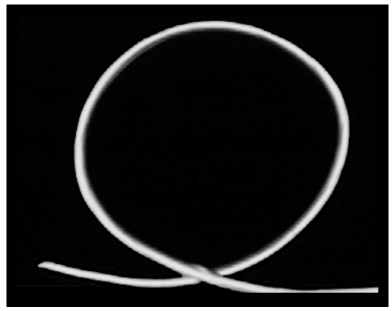

Fig. 2. Glow wire

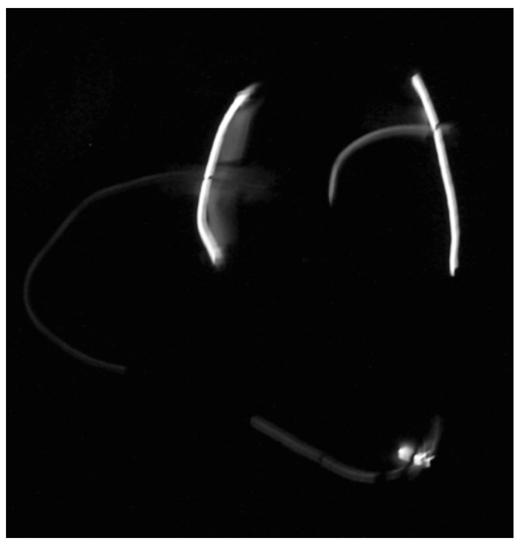

Fig. 3. The Illuminated Contour-Based Markers. Each pair of line segments illuminates a set of distinctive colours

2.2 The Body Suit

The assembled markers are attached to a body suit to be worn by the subject to be tracked during the motion capture procedure. In order for this body suit to support realistic and accurate tracking it requires some essential characteristics. First, it must not restrict the user's freedom of movement. Secondly, it is important that the material the bodysuit is constructed of is able to closely follow the movement of the tracked body and stay in place as the skin moves underneath [35]. After experimenting with different types of materials and suit designs, the researcher found that tight sitting, lightweight thermal underwear and socks have the above mentioned qualities

As the body suit needs to be washed after being used, the markers are designed to be temporarily attached to the suit using Velcro instead of being permanently attached. As such, strips of Velcro patches were glued to the suit at key positions so that the markers can be attached to them (how these key positions is selected in described below).

In order to allow for adjustments of the suit so that it could be accommodated for small variations in body size and shape, these patches of Velcro where made long enough to allow for fine tuning of marker positions. The complete bodysuit can be observed in Figure 4.

A small battery driven inverter that supplies the markers with electricity, is placed on the lower back region of the body suit. This location has been selected as it attributes minimal interference with the user's body movement.

Fig. 4. A prototype of the bodysuit with Illuminated Contour-Based Markers attached.

2.3 Marker Placement

To support a motion capturing process with minimum interference of noise, it is important to identify positions on the tracked body, which are suitable for marker attachment. These key positions should allow the markers to remain in stable relationships with the underlying skeleton as the body moves. One thing that can affect this relationship is secondary motions in soft body tissue [14, 36]. In order to avoid capturing these secondary movements, the researcher has chosen to place the markers on areas of the body where the skin is close to the bone (e.g. elbows, knees and wrist). Figure 5 shows a virtual skeleton rigged with a set of Illuminated Contour-Based Markers.

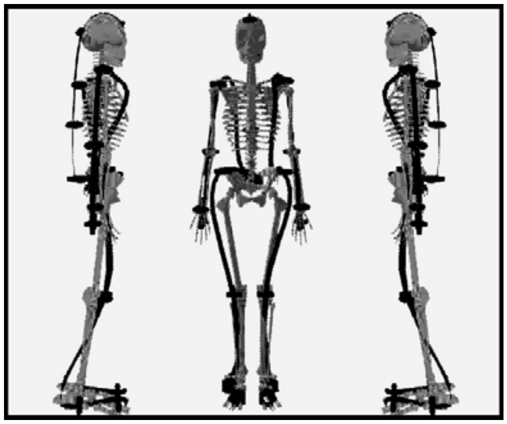

Fig. 5. Virtual skeleton rigged with Illuminated Contour-Based Markers.

2.4 The Motion Capture Images

Series of images has been captured of an articulated human body rigged with the Illuminated Contour-Based Markers. These images have an identical size of 720 x 576 pixels and the color space used is RGB. All images where captured using four different calibrated cameras, placed in a circle around the capturing volume. More colors appear in the captured images, than those used in the original Illuminated Contour-Based Markers System as a result of small differences in sensing devises within and across these cameras. This results in an excessive image complexity, which contributes to increasing processing time. To solve this problem each image is pre-processed (as explained in 2.5).

As image features change over time and across capturing devices and to ensure that the proposed system is able to process all features correctly, images used in experiments have been selected randomly across both cameras and time steps.

2.5 Data Pre-processing

To reduce the complexity of captured images, un-interesting image components are filtered out as background in pre-processing using a thresholding technique. Data that is valid for the main processing is compressed into a number of flat colour regions, corresponding to the number of colours used in the marker system. Tolerance values for each of these regions have been determined through multiple trial and error experiments.

2.6 Modified K-means Algorithm for Noise Filtering

When data has been pre-processed, the Modified K-means algorithm is used to clean up noise embedded in each image by creating clusters of pixels based on their relative spatial positions in the image. Following the classical K-means algorithm [27, 28, 37, 38, 39, 40, 41, 42, 43] the Euclidean Distance measure shown in Equation 1, is used to determine which cluster a pixel belongs to. Each pixel is put into a cluster, which yields the minimum Euclidean Distance between the pixel and the respective centroid. The centroid of each cluster is changed iteratively by calculating its new coordinate as the average of the sum of the coordinates of the pixels in the cluster until it converges to a stable coordinate with a stable set of member pixels in the cluster. For each iteration, the memberships of each cluster keep changing depending on the result of the Euclidean Distance calculation of each pixel against the new centroid coordinates.

$$d_{ic} = \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2} \tag{1}$$

where:

d_{ic} :the Euclidean distance between pixel i and a centroid c
x_i, y_i :the 2D coordinate of pixel i
x_c, y_c :the 2D coordinate of centroid c

The modifications to the classical K-means algorithm lie in the definition of a data vis-a-vis noise cluster and the automation of the determination of the optimum number of clusters an image should have. A cluster is considered noise if it only has a few pixels in it. The minimum number of pixels in a cluster, or the cluster size, should be set such that it minimizes the degree of false positives (i.e. data clusters incorrectly classified as noise) and false negatives (i.e. noise clusters incorrectly classified as data). The minimum cluster size is domain specific and is determined by observing the number of data points usually found in a noise cluster for the type of data at hand. In this experiment, the minimum number of pixels in a cluster is set to 4 after a few trial and error processes.

The compactness of a cluster is used to determine the optimum number of clusters for a given image. In this paper, the degree of compactness of a cluster is defined as the number of pixels occupying the region of a rectangle formed by the pixels located at the outer most positions of the cluster (i.e. the pixels that have the maximum and minimum X and Y coordinates respectively). A cluster that has a lower degree of compactness than the specified value will be split further. In this experiment, the degree of compactness used is 20%, which is a value just below the minimum compactness of valid data clusters for the observed domain.

The modified K-means algorithm performs local search using randomly generated initial centroid positions. It is a known problem that the determination of the initial centroid positions plays a big part in the resulting clusters and their compositions [29, 38, 44, 45, 46, 47]. In order to reduce this problem and to make the search mechanism a bit more exhaustive, ten clustering exercises using ten different initial centroid positions are performed for each image. The result of the exercise that produces clusters with the maximum total degree of compactness will be selected. If a set of data cannot be separated linearly we discard the run and initiate the algorithm again with different initial cluster positions. The processed data is finally plotted, in order to allow for easy inspection of results.

A detailed overview of the Modified K-means algorithm is presented in Table 1.

3 Experiment Results

In this Section we present results of experiments on pre-processing and intra-frame noise filtering in images captured from an articulated human body rigged with sets of Illuminated Contour-Based Markers.

3.1 Recognizing Coloured Line Segments

At present we have separated five of the ten different types of glow wires available on the market into distinct flat color regions in pre-processing, allowing ten different markers to be constructed. These recognized wires are classified as: Red, Orange, Green, Purple and Blue. Each of the remaining five wires appears to have color attributes, which are so similar to a number of the remaining nine, that they are hard to separate from the others. The separation problem is a result of sensing devices across cameras being slightly different because this makes it necessary to employ an un-naturally wide color threshold for each color, in order to support successful classification across cameras. This in turn makes the color space pre-maturely crowded leaving no room for the remaining five unclassified line segments.

3.2 Noise Filtering

Five types of experiments have been performed on the Modified K-means algorithm. The first experiment tests the algorithms ability to remove synthetic

Table 1. Modified K-means algorithm for noise reduction in optical motion capture data

```
Procedure: modified K-means algorithm for noise reduction in optical motion
capture data

  Set minimum number of data points per cluster // cluster size constraint
  Set minimum cluster compactness // cluster compactness constraint

  For a set number of experiments do

    Set initial cluster centroids

    Set interationFlag to yes
    While iterationFlag = yes do

      Set iterationFlag to no

      // Basic K-means
      Repeat
        Calculate the distance between data points and each cluster centroids
        Assign each data point to cluster
        Calculate the new cluster centroids
      Until all clusters have converged

      // Filter clusters based on minimum cluster size constraint
      For each cluster
        If cluster has too few data points then
          Delete cluster
        End if
      End For

      // Filter clusters based on cluster compactness constraint

      For each cluster
        // Find corners of compactness window
        Find data points with minimum and maximum X values
        Find data points with minimum and maximum Y values
        Define cluster compactness window size

        Calculate the number of data points in cluster
        Calculate cluster compactness = number of data points / compactness
        window size

        If cluster compactness < minimum compactness then
          Split cluster into two
          Set iterationFlag to yes
        Else
          Record cluster compactness
          Remove cluster and content from analysis
        End if
      End For

      If iterationFlag = no then
        Calculate the average compactness of all clusters in the experiment
      End if
    End while
  End For

  Select set of clusters from experiment with the highest average compactness
End Procedure
```

spike noise from raw motion capture images. The second aims to find the algorithms tolerated spike noise level. This is done by introducing images with different levels of real spike noise to the algorithm and analyzing the output. The third, tests how well the algorithm deals with real noise that has different Gaussian blur radii. This experiment is conducted in order to estimate the algorithms ability to remove noise with different Gaussian characteristics. The fourth type of experiment is a set of comparisons between a commercially available Median filter [48], which is used for reducing noise in images and the proposed modified K-means algorithm [4]. Finally it is shown that the proposed modified K-means algorithm also can be used to remove noise in images with Classical spherical markers.

Removing Synthetic and Real Spike Noise

In the first experiment an image with spurious artificial spike noise has been cleaned. The result of this experiment can be observed in Figure 6, where the noisy image is represented in the top (noisy pixels are encircled) and the cleaned version in the bottom. Here the white pixels represent the background while the black pixels represent the components of the Illuminated Contour-Based Markers System and noise.

Three of the images used in the second experiment, which involves finding the Modified K-means algorithms spike noise level tolerance is shown in Figure 7. Here the leftmost image has 0%, the middle 8% and the rightmost 16% real spike noise (image contrast is increased in order to allow for easy inspection).

Figure 8 shows the results of the experiment on real spike noise. The number of cleaned data points is displayed vertically, while the noise level is displayed horizontally in percentage. One can here observe that more than fifty percent of the original data points still are classified correctly at a noise level of 8%, while the algorithm still proved to effectively remove noise in images with noise levels up to 12%.

Removing Gaussian Noise

In this experiment, Gaussian blur with varying radii is introduced to several copies of the noisy image in the top of Figure 6, before the Modified K-means algorithm is used to clean the images. In Figure 9, three of the processed images are presented (the leftmost image has a Gaussian blur pixel radius of 0, the middle a radius of 2, and the rightmost 4).

Figure 10 shows how much data that can be recaptured after noise with Gaussian characteristics has been removed. One can here observe that the number of data points recaptured naturally decreases as the radius of the Gaussian blur increases. However, it is also shown that the degradation of performance occurs gradually, as oppose to abruptly when the radius is increased up to 2.5 pixels. For this reason, it can be concluded that the modified

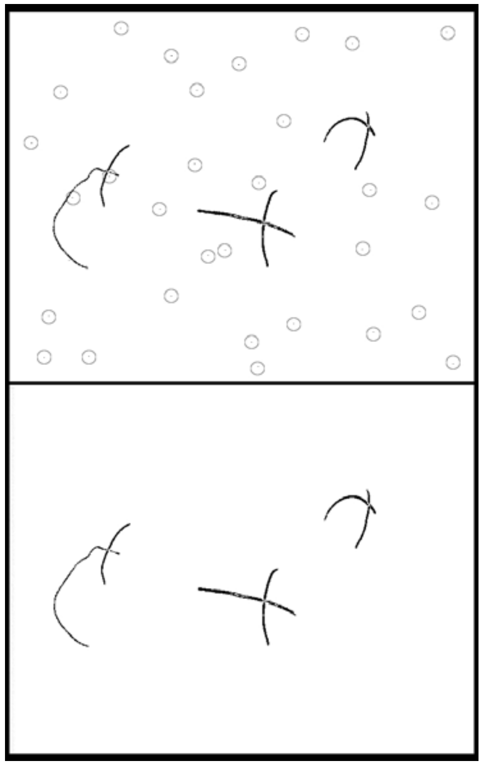

Fig. 6. *Top:* A pre-processed motion capture image and noise in the form of irregular lighting can be observed. *Bottom:* The resulting cleaned image with noise removed

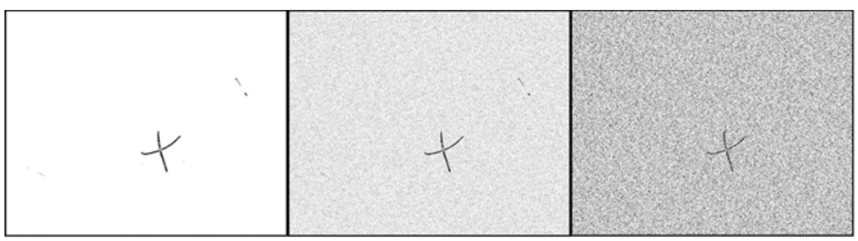

Fig. 7. Images with Illuminated Contour-Based Markers and Spike noise of 0, 8 and 16%.

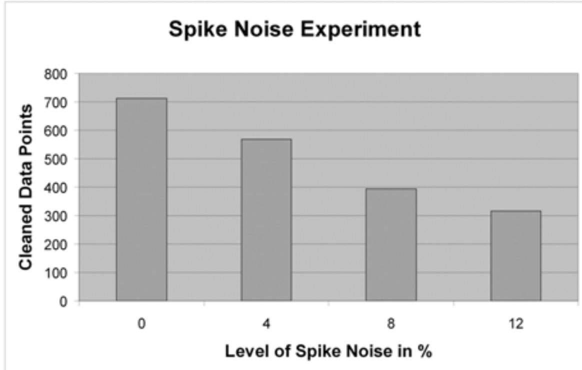

Fig. 8. Results from experiment on images with Illuminated Contour-Based Markers and Spike noise of 0, 4, 8 and 12%.

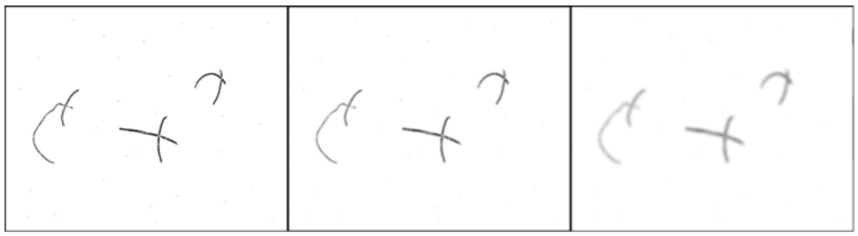

Fig. 9. Flattened images with Gaussian blur of 0, 2 and 4 pixels in radius before noise is removed.

K-means is capable of removing noise with Gaussian characteristics while keeping false positives to the minimum. This result is better than the performance of the Mean and Median filters that are well known to only suppress (i.e. reduce) Gaussian noise rather than remove it [31].

3.3 Comparisons: Modified K-means vs. Median Filter

Two types of comparisons have been conducted and both of these have been between a commercially available Median filter [48] that is used for reducing noise in images and the proposed modified K-means algorithm [4].

Spike Noise Removal Comparisons

In Figure 11 one can observe results of an experiment where the two algorithms ability to remove spike noise is analyzed. The level of Spike noise is incrementally increased with 4% across four runs, starting at 0. The ideal number of data points after noise filtering is 747. All data is initially pre-processed. One can observe that the number of recaptured data points is lower for the

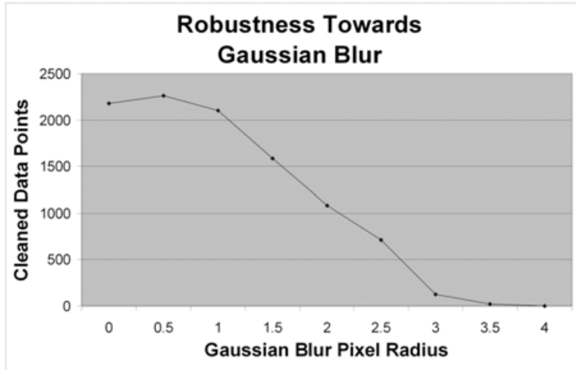

Fig. 10. Cleaned data points recaptured after the removal of Gaussian blur noise with varying radii using the Modified K-means.

Median filter in all test runs. This indicates that the modified K-means algorithm removes spike noise with a lower number of false positives than the Median filter. This indication is verified in Figure 12, where the number of false positives across the same four runs in presented. One can observe that there are strong correlations between the increasing number of false positives and the level of Spike noise. The number of false negatives was at zero across all runs.

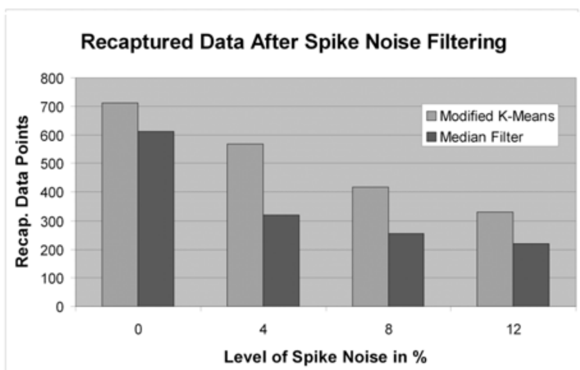

Fig. 11. Recaptured data after Spike noise filtering.

Gaussian Noise Removal Comparisons

In Figure 13 results from an experiment on a series of motion capture images with noise and increasing levels of Gaussian blur is presented. The Gaussian

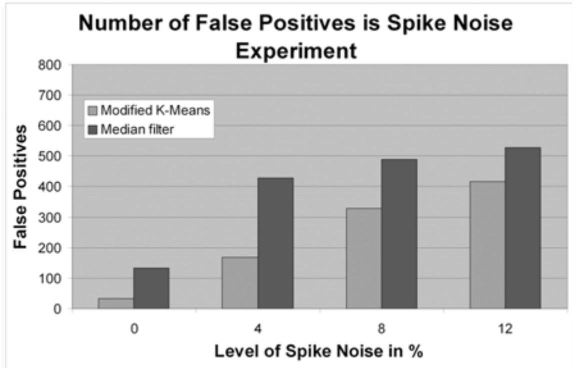

Fig. 12. Number of false positives in Spike noise experiments.

blur pixel radius is increased incrementally with 0, 5 pixel across 8 runs, starting at 0 pixel radius. One can observe that there are close correlations between the performance of the modified K-means algorithm and the Median filter as the blur levels increase. One can also observe that the number of correctly recaptured clean data points decrease gradually as the Gaussian blur radius increase.

Figure 14 show how the number of false positives increase as the Gaussian blur pixel radius becomes greater. One can observe that there are strong correlations between results from the modified K-means algorithm and the Median filter also here. The number false positives is here, still below fifty percent of the total number of data points when the Gaussian blur pixel radius is at 2 pixels.

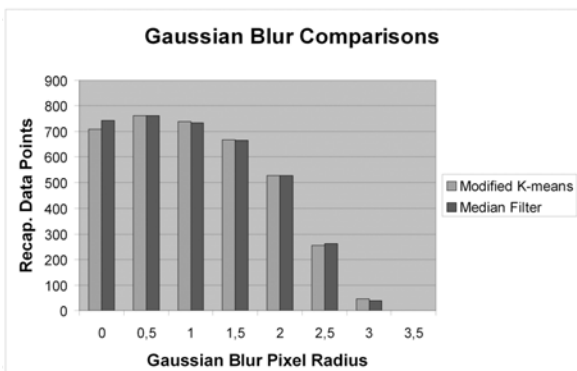

Fig. 13. Number of recaptured data points after images with noise and varying levels of Gaussian blur have been cleaned.

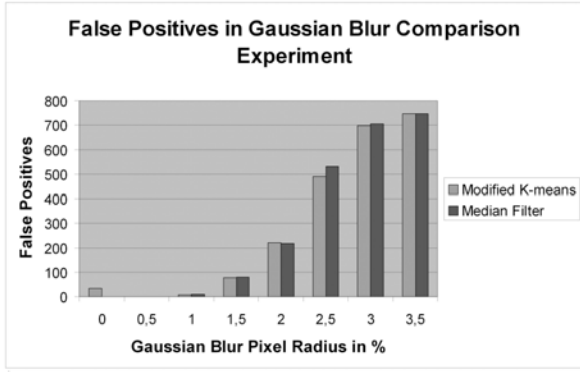

Fig. 14. Number of false positives as the Gaussian blur radius increases.

In Figure 15 one can observe the number of false negatives in the same experiments as above. One can observe that the number of false negatives peak at o.5 Gaussian blur pixel radius for both the Median filter and the modified K-means algorithm. This peak is at the same point where the number of false positives is at its lowest.

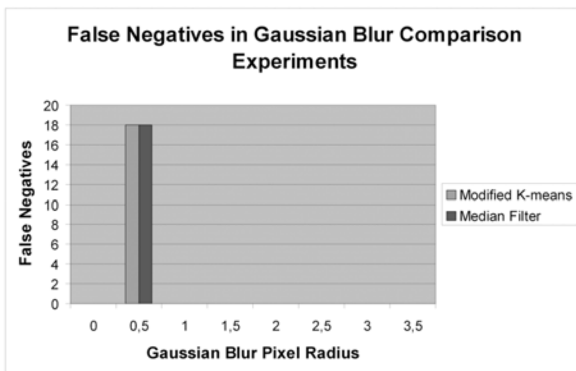

Fig. 15. Number of false negatives as the level of Gaussian blur increases.

3.4 Removing Noise in Images with Spherical Markers

The Modified K-means algorithm has also been tested on images with synthetic Classical ball style markers, these experiments show that the proposed algorithm also is capable of cleaning this type of data. An illustration of one the results are given in Figure 16, where the original image is presented to the left and the processed image to the right.

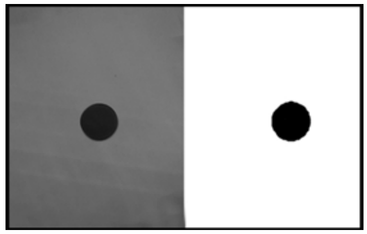

Fig. 16. *Left:* A raw image generated from a synthetic ball marker. *Right:* The image with noise removed.

3.5 Processing Time

It is important to notice that processing time increases with each additional cluster centroid needed to analyze a dataset. Experiments show that if the level of noise is at 16% and above (this number is dependent on the color composition of the noise at hand and the threshold values set for each marker component in pre-segmentation), the calculation time becomes so great (when using one Pentium 4 processor) that the noise cleaning becomes impractical. This problem can be dealt with in three ways. The first is to ensure that capturing sensors and tools used for data transfer support lowest possible interference of noise. The second method, which only partially solves the problem, is to increase the value for the minimum number of data points per cluster constraint, such that more noisy data points can be removed from the dataset using a smaller number of cluster centroids. Here, it is important to notice that when the constraint value becomes greater than the number of data points usually clustered together in valid data, the number of false positives will increase. The third method for solving the problem would be to increase processing power.

4 Conclusion

A set of Illuminated Contour-Based Markers for optical motion capture has been presented along with a modified K-means algorithm that can be used for removing inter-frame noise. The new markers appear to have features that solve and/or reduce several of the drawbacks associated with other marker systems currently available for optical motion capture. Some of these features are:

- missing data can be estimated both inter-frame and intra-frame, which reduces the chances of complete marker occlusions without increasing the number of cameras used.
- system is robust toward changes in external lighting compared to markers that do not produce its own internal light.

- markers can be automatically identified in one single image.
- eliminates the need for synchronizing camera shutters with flashing from markers and therefore allows for tracking without wiring the markers to a complex computer.
- has the potential to generate more markers than systems, which use only one single color for marker identification.

In the modified K-means algorithm, the modifications to the Classical K-means algorithm are in the form of constraints on the compactness and the number of data points per cluster. Here clusters with a small number of data points are regarded as noise, while sparse clusters are split further. The value for the minimum number of data points per cluster constraint is domain specific and is determined by observing the number of data points usually found in a noise cluster for the type of data at hand. The value for the minimum compactness constraint should be set just below the minimum compactness of valid data clusters for the domain. Several experiments have been conducted on the noise filtering algorithm and these show that flattening the images into six color regions in the data pre-processing stage assists further processing by reducing the number of dimensions the algorithm must cluster. Experiments also indicate that the modified K-means algorithm:

- manage to clean artificial and real spike noise in motion capture images with Illuminated Contour-Based Markers or Classical spherical markers when the signal to noise ratio is up to 12%.
- is capable of completely removing Gaussian noise with a gradually increase in false positives as the radius increases. This is a better result than that produced by traditional Median and Mean filters.
- reduces Spike noise in images with Illuminated Contour-Based Markers in a way that results in less false positives than the Median filter is capable of.
- reduces Gaussian blur in images with Illuminated Contour-Based Markers with similar number of false positives as the Median filter.

5 Future Work

A suitable algorithm for automatic marker midpoint estimation is currently being constructed. When a complete set of experiment have been conducted, future research will involve investigating a color calibration method, which aims to synchronize the input from capturing cameras. This in order to allow more markers with distinctive color combinations to be generated. This calibration procedure will involve comparing the color values being registered for the same object across cameras. Trough the use of knowledge obtained trough these comparisons, a correction matrix that can be used for guiding the synchronization of input from different cameras, can be generated. This synchronization process may in turn allow for smaller regions of the color space to be assigned for classification of each marker component, resulting in a less crowded color space. This optimized use of color space may make room for new distinctive regions within the color space, which can be used for classifying more of the ten glow wires currently available on the market. It may also prove fruitful to research into the use of a color space that has a separate channel for luminosity, (such as Absolute RGB or HSV) so that luminosity information can be removed from further analysis. The benefit would be that the color values registered for each glow wire would be more stable as the distance between wires and cameras change. This may in turn allow for smaller regions of the color space to be associated with each wire, allowing further optimization of the color space separation.

When the above is completed, the research focus will be on investigating methods that allow for automatic 2D to 3D conversion of marker coordinates. This before focus is shifted onto researching and implementing techniques that allows a virtual skeleton to be fitted to incoming motion data and tracked over time. Finally, ideal motion models will be captured and the intelligent motion recognition system designed, before the second major research phase, (which involves constructing the Multipresence system described by the author in [1, 2]) is initiated.

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