

# BallotX - Automated Ballot Paper Counting System

M.N.M. Azhar, D.R.M.G.M. Rathnayake, A.I.V. Madusanka, L.Rajapakshe  
C.R. De Silva and Shanaka Ransiri

Department of Computer Science and Engineering, University of Moratuwa, Sri Lanka.

**Abstract**— Even though the technology has evolved dramatically throughout the last decade or so, many countries have stuck with the traditional ballot paper counting process. With BallotX we propose a viable alternative to reduce time and resources consumed in the traditional manual process by introducing image processing into this domain. This research paper discusses the ways in which the above can be achieved for varying ballot papers and elections. It also addresses the issues of transparency and reliability which has top priority when transforming such sensitive manual process to an automated one

## I. INTRODUCTION

The field of Image processing serves today's applications in many ways. The application of Image Processing techniques has played an important role in areas like security, speed detection and even astronomy. In today's competitive and fast moving world, time and accuracy has become the most important assets in any industry. There are several areas in the modern world where the current Image Processing knowledge can be put in to good use in order to transform traditional, manual processes to more efficient semi automated ones. Since in many countries, using a ballot paper to cast the vote has been a well established but time consuming process for decades, the process can be improved for higher efficiency by using technology to good effect.

BallotX is a research project carried out to integrate image processing features into ballot paper counting for the purpose of eliminating bottlenecks present in traditional manual process. This approach increases performance, accuracy and much needed transparency by introducing image processing.

The common problems in the field of image processing applications are the difficulty of achieving 100% accuracy and it is the most significant factor that should be considered when it comes to automating the process using image processing techniques. It is important to identify and extract the necessary information from the image and distinguish unwanted noise that could be generated due to bad handling while storing and transporting and scanning ballot papers before counting. Given the sensitivity of the process it is important to make sure that the verifiability of the results is maintained.

BallotX solves the set back of accuracy by introducing dual algorithm verification and the calibration modules which will be discussed in detail in this paper. It consists of three major

modules; Calibration module, Data Extraction module and the Result Generation Module.

## II. METHODOLOGY

The main image processing techniques we have used in our research are pattern matching, length extraction and mark recognition. Basic theoretical concepts of these techniques are explained in detail in this section. We will focus our discussion on algorithms and methodologies we chose to use and the reasons behind those selections. Main concentration will be on the calibration and Data Extraction modules since image processing techniques are mainly applied on those modules.

### 2.1 Overall Process

A sample image of the ballot paper used will be scanned and calibrated to identify the respective regions of interest for parties and preferences. The scanned images of the marked ballot papers will be checked for votes and preferences in pre calibrated regions of interests. The extracted information will be evaluated for legitimacy and the result will be stored. Finally results and the required reports will be generated.

### 2.2 Calibration

Ballot paper consists of set of parties (symbol with party name), voting regions, preferential marking regions and a serial number. Before extracting party and preference vote, segmenting the ballot paper into regions of interest and mapping party and preferential number are defined as the calibration. First step is to detect skew angle and de-skew the image. Hough Transformation [5] based skew detection method is applied in developing the application. Next, scan line methods, length extraction [2] is used to segment regions. Discovered lines are filtered using characteristics of the ballot paper and gathered information of the ballot paper such as number of parties and number of preferences from the user. Finally user assisted mapping of ROIs to parties are done. This process can also be fully automated by predefining required information such as order of parties. All the coordinates and mappings are encrypted and saved in configuration xml file for the use of vote identification. According to the current processes and procedures of the elections in Sri Lanka, main five elections are included in the system. For each election type, the calibration process varies considerably. At this step of calibration, chosen election specific details such as number of parties contested and number of preferences contested are gathered for future processing of the calibration. Failure to complete accurate information in this step causes the calibration process to

restart. Main steps in the calibration process are described in detail in the following sections.

1) *Election type selection*: According to the current processes and procedures of the elections in Sri Lanka, there are five main types of elections. For each election type, the calibration process varies considerably. At this step of calibration, chosen election specific details such as number of parties contested and number of preferences contested are gathered for future processing of the calibration.

2) *Serial number validation*: System needs to ensure that each ballot paper is tested against serial number ranges, marked and results are saved. As a result calibration of the serial number location is essential. The region in which the serial number can be found is configured in this step.

3) *Party calibration and mapping*: Calibration of contesting parties and mapping their respective party names is considered to be the most important step in calibration process. The system automatically detects duplicate regions and conflicting regions and restricts the user from adding faulty information to a certain extent. After the configuration of all required regions are completed by the administrator, the system will visualize the configured parameters in a provided sample ballot paper, hence it is possible to identify if any errors have been made during the mapping process before confirming.

4) *Preferences calibration and mapping*: This step is similar to party calibration and mapping, however the preferences are mapped as numbers. All the region of interests are mapped and number of regions are compared with preference count selected at the second phase of the calibration process. Here the mapping the respective ROIs to the respective numbers are done automatically.

5) *Mapping confirmation*: This step is introduced to get the overall mappings into ballot paper and get the user confirmation. At this level, all the errors or wrong mappings should be identified by the user/administrator and if errors exist, user/administrator should start calibration process again. All the previous calibration steps need to be followed again to ensure that no erroneous configuration is accepted.

6) *Test run*: To start the bulk processing of ballot papers, randomly selected ballot images are tested and summary of the results are shown to the user/administrator. The user/administrator can take a decision on the statistics of the results to continue with the current configuration of the system or to recalibrate the system.

7) *User acceptance and confirmation*: Final step of calibration process is to make sure that the system is properly calibrated and ready to use in counting process. When this process is completed, the calibration module is freeze so that recalibration is no more available. At this point onwards, bulk ballot processing is allowed with the calibrated data collected.

### 2.3 Vote Recognition

Party vote recognition is done using dual algorithms, Length extraction and Pattern matching. In order to extract the necessary information the unwanted noise is minimized or eliminated. It should be noted that for efficient and accurate extraction of information; the data should be isolated and distinguished from the noise that is created by the scanner or

the mishandling of the paper prior to scanning. To achieve that requirement, the images of the ballot papers have to go through three major steps which will be described below.

1) *Preprocessing*: BallotX converts the scanned ballot paper to binary form in order to rectify the effect of noise. This conversion is critical since, the possible loss of data should not affect the information extraction process. Image binarization, which is also called image thresholding, is a simple but effective way of separating the objects from the background. Before the ballot image is binarized it needs to be converted to a gray scale image. Then the image should be binarized at a threshold that is optimum to the relevant image. The problem with thresholding is that we consider only the intensity values, not the relationship between pixels. To set a global threshold or to adapt a local threshold to an area, we usually look at the histogram to see if we can find two or more distinct modes—one for the foreground and one for the background. BallotX uses Otsu's method of thresholding to find the threshold value automatically. The Otsu filter is a filter that takes an image and from its histogram calculates the values at which the image should be thresholded to accomplish an optimal separation of a foreground and background objects [6]. Because Otsu threshold operates on histograms it's quite fast. Speed here is a significant requirement since the threshold should be identified for each and every ballot paper at the time of processing. It has a slight disadvantage since the algorithm assumes uniform illumination though the image and the histogram should be bimodal in order to find a proper threshold. But since the ballot used are only to colored, that disadvantage does not have a significant effect in this system.

2) *De-Skew Images*: As it is mentioned in the previous sections, there is a calibration process in which the regions of interest are configured using a sample image of an empty ballot paper. But those configured areas can vary due to errors made when feeding the ballot papers to the scanner. Thus it is necessary to detect the skew angle of each and every image and then make the skew correction. Once the images are binarized, those are subjected to skew detection prior to processing. The process starts with finding the reference lines in the image using Hough transformation. Then the angles of the lines are detected in the normal form, in which perpendicular distance from the origin and the angle is taken in to consideration. Once the angles of the lines are calculated, the skew angle is calculated as the average of all the angles of lines. In our process Hough transform based line detection methods are used since lines are not exactly horizontal or vertical due to the skew that has occurred in scanning. It is necessary to limit the skew correction to a certain degree, due to performance constrains. But it is also necessary to choose the upper bound of correction in such a way that would not result in wrong conclusions. In BallotX we have limited the angle to 18 degrees to reduce the running time. This limitation does not make any impact because today's industrial scanners detect skew angles of about 5 degrees.

3) *Extract Information*: The relevant regions of interest of the bit-mapped representation of the scanned image are subjected to run length extraction for each scan line. By

repeating the process both column and row wise marks can be identified. In order to identify the unintentional correlations between neighboring regions, run length extraction is repeated in an internal sub region within the main region of interest. A threshold of ratio between the length extractions values are taken to determine if the mark is intentional and is regarded as a casted vote. Since the voting system in Sri Lanka is complicated with the preferential system, it is common to find many errors in voting. Therefore if the system rejects all the votes with minimal errors without considering the intention of the voter to a certain extent, it could result in many votes which would have been accounted in a manual system could be rejected. Thus identification of correlation is significant. There can be certain scenarios in which the system cannot decide with confidence if the vote or the preference should be rejected or not. In such cases those images are stored separately to be verified by an authorized person. Once the manual verification and decision making is completed, the results of those doubtful ballot papers will be recorded with an extra record to keep track of the person who entered the results.

The second algorithm in the dual algorithms approach is Pattern matching which is an elementary tool in the field of image processing [4]. Pattern recognition problem can be classified as recognition of a specific object in the presence of all other objects [3]. In the context of ballot paper counting pattern matching is used to identify a cross mark in the pre defined regions of interest of the bit-mapped representation of the scanned ballot paper image. The open computer vision library which is the main image processing library we are using, accommodates three distinct pattern matching techniques namely, square difference matching, correlation matching and correlation coefficient matching with normalized methods for each of the above to ignore the effect of lighting differences in the input samples. Normalized correlation coefficient matching was employed in the pattern matching algorithm, which is represented as

$$R(X, Y)_{ccoeffnormed} = \frac{R(X, Y)_{ccoeff}}{Z(X, Y)} \quad (1)$$

Where,

$$R(X, Y)_{ccoeff} = \sum_{x, y} [T(x', y') \cdot I(x + x', y + y')]^2 \quad (2)$$

And,

$$Z(X, Y) = \sqrt{\sum_{x, y} T(x', y')^2 \cdot \sum_{x, y} I(x + x', y + y')^2} \quad (3)$$

$R(X, Y)_{ccoeff}$  – Resultant correlation coefficient image

$T(X, Y)$  – Template image

$I(X, Y)$  – Input image

So a perfect match would yield  $R(X, Y) = 1$  while a perfect mismatch of that would be  $-1$ . [1]. The grayscale pattern matching method recognizes each pixel of a reference image pattern as one of 256 levels of gray, and it compares this data with the information of the image on the screen to detect the position. However, with this method accurate position detection is sometimes difficult because the absolute value of the gray scale data is easily affected by variations in ambient light.

The normalized correlation method allows for stable pattern matching without being affected by ambient light. The average brightness of the whole image is subtracted from the brightness (grayscale data) of each pixel for both the reference image and input image. This is called normalization, which eliminates the difference in the brightness of both whole images. Then, the image is located at the position where the patterns of the reference and input images best match (i.e. highest correlation), and the position of the target pattern in the image is accurately detected.

Here we analyze the region of interest for a cross mark using a template of a conventional cross. BallotX identifies the cross mark by performing a co-relation normalization pattern match on the ROI.

Preference vote recognition is done using the dual algorithm approach with subtle variations. Since the preference number is already printed in the region of interest, bit-map representation of the image should be altered in order to distinguish between a vote mark and the existing number. The existing numbers are eliminated by subjecting the region of interest to background subtraction [3] by means of the pre calibrated sample image. Even though the pixel counting technique along with the correlation correction can be directly applied here, the second algorithm, pattern matching did not give reliable results. Therefore we choose to change the second approach to line detection. We used Hough transforms for line detection. The advantage of the Hough transform is that the pixels lying on one line need not all be contiguous. This can be very useful when trying to detect lines with short breaks in them due to noise, or when objects are partially occluded, which exactly is the case when we consider this scenario.

#### 2.4 Serial number recognition

Optical character recognition is used to identify the serial number of each ballot paper. Serial numbers can be identified by analysing the calibrated region. In order to protect privacy, the serial numbers are not revealed to the users of the system. Serial numbers are used to verify the legitimacy of the ballot papers. This can be used to identify forge ballot papers since the serial number is unique and the system can be preconfigured to process only the ballot papers which's serial number is within the specified range.

#### 2.5 Random vote verification

Once the counting is done using any automated ballot counting system there is speculation of fraud and mistrust.

BallotX addresses this issue with the Random vote verification module. It allows the authorize representatives of the contesters to choose some images randomly from the batch of scanned images and enter its serial number into the system and view the result that has been extracted by the system for that respective ballot paper. This random verification mechanism provides much necessary transparency in to BallotX.

### 2.6 Report generation

Report generation is a common and very trivial module in the system. Once the data has been processed and extracted those information is stored in a database. Thus various report generation modules can be plugged in to the system according to the requirement.

## III. RESULT & DISCUSSION

### 3.1 Efficiency/speed

Average number of ballot papers counted per hour exceeds 60000 using an average PC with the configuration of 2 cores of 2.1 GHz, 2GB of Random Access Memory. This number increases when the number of ballot papers to be counted is higher, since the initial configuration time is independent of the number of images processed. Both preference votes and party votes are counted simultaneously to increase efficiency. These performance measures can be obviously increased under better configurations.

### 3.2 Accuracy

Both party and preference votes are verified with dual algorithms to ensure 100% accuracy. Pattern matching method is selected favoring accuracy over speed. The following table indicate the related figures.

TABLE I  
ACCURACY STATISTICS

Algorithm	Avg. Ballot papers/second (Single threaded)	Accuracy % (with best threshold)
Square Difference matching	20	72
Correlation matching	18	86
Correlation Coefficient matching	15	96

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