# Laban Movement Analysis using Kinect

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"Man moves in order to satisfy a need." —Rudolph Laban

## Abstract

**Laban Movement Analysis (LMA) is a method for describing, interpreting and documenting all varieties of human movement. Analyzing movements using LMA is advantageous over kinematic description, as it captures their qualitative aspects in addition to the quantitative. Thus, in recent years, LMA is increasingly becoming the preferred method for movement analysis. In this study we developed a Machine Learning (ML) method for recognizing Laban qualities from a markerless Motion Capture (MOCAP) camera — Microsoft's Kinect. We believe that we are the first succeeded identifying LMA with a ubiquitous sensor. There no papers similar enough to ours for a performance comparison, but our work obtained a recall and precision rate of about 60% averaged over the qualities, result that is a solid foundation for a future work, and even a success by itself.**

## 1 Introduction

Our goal is to create a method for automated identification of Laban qualities that characterize any movement sequence, using Kinect. Our problem presents three challenges. The first is quantifying subtle qualities for which a well-defined quantification has not yet been found. The second challenge is handling noisy sensory data with an in-home setup, and the third is keeping our method as general as possible — We are developing a system capable of handling different scenarios (dancing and acting, for example), and different postures (sitting and standing, for example), by different people of different backgrounds (if any) in movement.

We propose a low-cost (100$), non-intrusive (markerless), ubiquitous (76 million sensors around the world) system that can recognize Laban qualities using the Kinect sensor and Software Development Kit (SDK). For evaluation, we have created our own dataset and applied several ML techniques on it, in several learning settings. We chose to use ML (instead of rule based algorithms), so we would be able to use all of the rich data provided by the Kinect sensor rather than focus on a very subtle feature extraction method that requires domain expertise. Using ML gave us an opportunity to reverse engineer the learned models and learn about our problem's intrinsic characteristics, such as which features are predictive of which qualities. The system obtained a recall and precision rate of between 40-60% in the more subtle qualities, and 60-90% in the more expressive ones.

### 1.1 Motivation for Automated LMA

There are numerous applications for computerized identification of the qualities that characterize each possible human movement. Examples include the generation and control of specific expressive movements of avatars, virtual characters, or robots in mixed reality scenarios [14]; detection of personality traits during a job interview [17]; early detection, severity assessment or revealing of genetic tendency (phenotype) towards various illnesses such as Alzheimer's, autism, Parkinson's disease [2], or schizophrenia, based on analysis of the person's motor behavior. Automated emotion recognition from movement is another important application, which may have a variety of uses such as online feedback to presenters to help them convey through their body language the emotional message they want to communicate (e.g., politicians and public speakers or actors in training) [5]; or recognition of people's emotions during interactive games such as those played using the Xbox [21].

For reducing our data collection and analysis effort, we focused our work on 18 Laban qualities (as listed in table 3) that have been found predictive for emotional state [23].

### 1.2 Laban movement analysis

LMA is a formal language for motion description first developed by Rudolf Laban [13] and colleagues in the middle of the 20th century. LMA describes both conscious and unconscious human movement, based on Laban's categories of *Body*, *Effort*, *Shape*, and *Space*. LMA has been used in the fields of dance, acting, athletics, physical therapy, and psychology and behavioral science. LMA helps actors create momentary moods and portray personality traits through movement. For example, LMA work investigates the *Effort* properties *Flow*, *Space*, *Time* and *Weight* of all movement and helps actors think specifically about why their character might move in a jerky, fast, light and direct manner versus a heavy, slow, indirect and uninterrupted manner. The entire LMA hierarchy is shown in figure 1.

### 1.3 Kinect Sensor Data

Figure 2 shows the skeleton provided by Kinect's SDK. Once the skeleton is detected, the 3D coordinates of all the joints of the

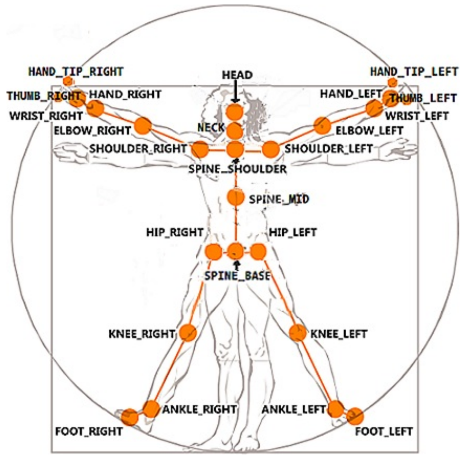


Figure 2: Skeleton positions relative to the human body

user's body — with the exception of joints that are not visible (e.g., a user's hand is behind his or her back) — are provided. As seen in Figure 3, the coordinates are in a "real-world" coordinate system, whose origin [0,0,0] is in the sensor and whose x-, y-, and z-axis are as depicted below.

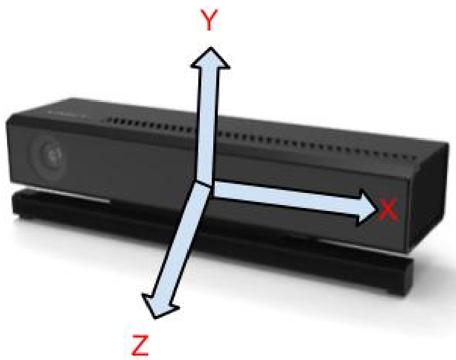


Figure 3: Kinect Coordinate System

### 1.4 Related Work

Several attempts were made to recognize Laban qualities. The first was Chi et al. [1], who quantified *Effort* and *Shape* for animation. Most of the other attempts were for emotion recognition in the context of Human Robot Interaction (HRI). Martin et al. [8] analyzed the importance of gestures in emotion recognition for HRI. Masuda et al. generated emotional body motion for a human form robot [14]. Rett et al. proposed a human motion recognition system using a Bayesian

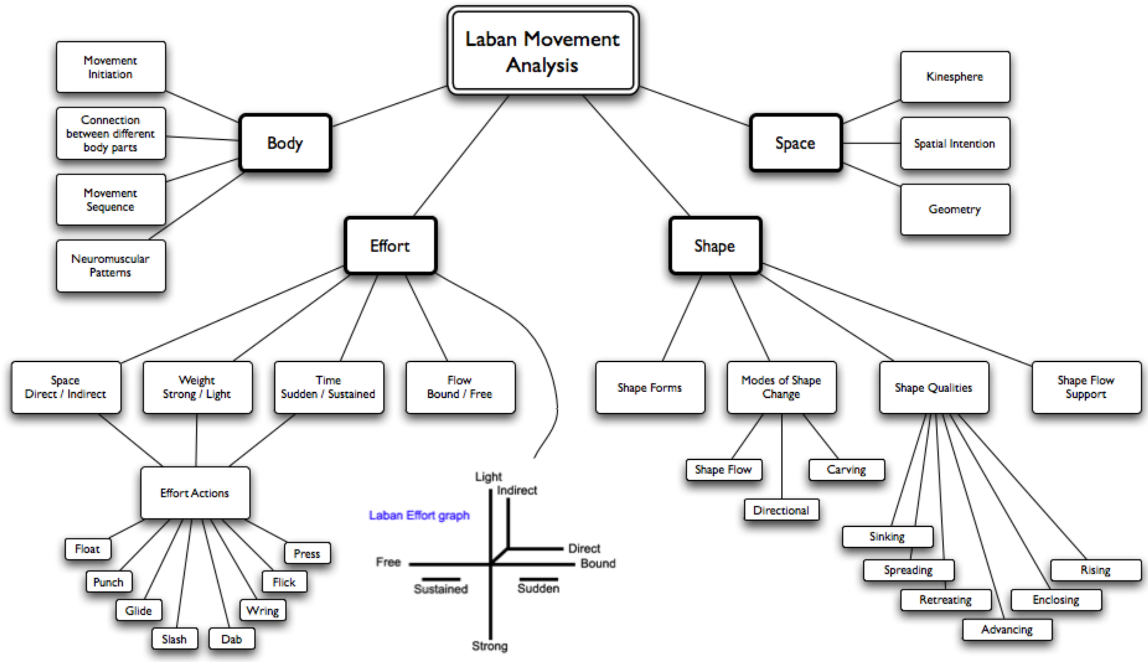


Figure 1: Main axes of LMA. Taken from [22]

reasoning framework [20]. The second line of works focused on LMA (not on emotions), but not using Kinect. Lourens et al. [3] used video data and Samadani et al. [4] used a high quality MOCAP camera, but both of them analyzed only hand gestures. A third line of works used Kinect as the main sensor for skeletal information. Gabel et al. [11] used Kinect for gait analysis. The work of Zacharatos et al. [21] was inspired by LMA for emotion recognition using Kinect. His feature extraction method was influenced by LMA principles, but he did not attempt to recognize the qualities themselves. Kim et al. [16] did attempt to do so but not on a real dataset and their work did not include a performance evaluation.

# 2 Method

Because we are the first to handle Laban recognition with Kinect, we had to create a dataset from scratch. To reduce the noise, and ensure that we capture the essence of the Laban qualities in our dataset, we decided that most of it should be built by recording several Certified [Laban] Movement Analysts (CMA), with just a few validation clips taken from recordings of ordinary people. We did not want to constrain the lengths of the clips to be equal, so in order to get feature vectors of uniform length (regardless of the original length of the clips), every feature is function of a whole clip (for example, the variability of the elbow's acceleration). On the uniform length feature vector we applied feature selection, single task learning (learning a model for every quality separately), and multitask learning (learning a model for all the qualities together).

## 2.1 Clip Collection

Two main datasets were collected:

- CMA dataset - includes 6 CMAs performing in about 80 clips each (a total of 550 clips). Every clip is about 3 seconds long, and the CMAs executed combinations of the 18 qualities. To achieve uniform distribution of the Laban qualities over the dataset, in every clip the CMA was asked to perform actions that include several specific qualities, and nothing but them.

- Non-CMA dataset - includes 2 subjects without a background in movement analysis, performing 30 clips each. Every clip

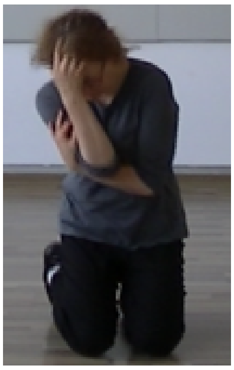

Figure 4: CMA during a clip

is also about 3 seconds long, and the subject was asked to perform one out of several tasks.

## 2.2 Clip Labeling

To achieve a ground truth labeling for the two datasets, every clip was tagged by a committee of 2 CMAs who determined which Laban qualities appear in the clip. The use of a committee decision instead of the subjective opinion of one CMA decreases the labeling noise and the decision is considered as ground truth.

## 2.3 Feature Extraction

Due to the unequal length of clips, all the extracted features are in whole clip granularity. We extracted two groups of features, the first is a relatively small, and contains about 100 features that each one of them is designed for a specific quality. The second group contains about 6000 features, and exploits the rich data that is provided by Kinect, by extracting from every joint in the skeleton, the angular velocity, acceleration, and jerk. For every joint/metric pair, the mean, variance, skew, and kurtosis were extracted (the extraction of the last four moments is denoted as $\phi$).

We denote $\vec{P}_j(t)$ as the vector (as we get it from the Kinect) of the position of joint $j$ in time $t$ in a clip with $n$ frames, and $\alpha_j$ is a coefficient proportional to the mass around the joint.

### 2.3.1 Shape Analysis: Sagittal Plane

Laban shape analysis of the sagittal plane is based on the distinction between two qualities, *Advance* and *Retreat*. This distinction was quantified by projecting the velocity vector of the Center of Mass (CM) on the vector of the front of the body. The CM was approximated in this case by the average of all the joints. The front of the body was approximated by the perpendicular vector to the vector between the Left Shoulder (LS) and the Right Shoulder (RS).

If *sag* stands for sagittal, then from the definition of CM of a physical system,

$\vec{P}_{CM}(t) = \sum_{j \in Joints} \alpha_j \vec{P}_j(t)$,

$\vec{P}_{shoulders}(t) = \vec{P}_{LS}(t) - \vec{P}_{RS}(t)$,

the front is perpendicular to $\vec{P}_{shoulders}$, so we can easily calculate it with:

$$\vec{P}_{front} = \vec{P}_{shoulders} \begin{pmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ -1 & 0 & 0 \end{pmatrix},$$

$S_{sag}(t) = \vec{P}_{CM}(t) \cdot \vec{P}_{front}(t)$,

$\vec{F}_{sag} = \phi([S_{sag}(1), \ldots S_{sag}(n)])$,

where $\phi$ was denoted in the beginning of the section.

### 2.3.2 Shape Analysis: Horizontal Axis

Here the distinction is between *Spreading* and *Enclosing* on the horizontal axis. This distinction was quantified by measuring the average distance between every joint to the vertical axis of the body that extends from the Head (H) to the Spine Base (SB).

$d_j = \frac{|(\vec{P}_j - \vec{P}_{SB}) \times (\vec{P}_j - \vec{P}_H)|}{|\vec{P}_H - \vec{P}_{SB}|}$,

$S_{horiz}(t) = \sum_{j \in Joints} d_j(t)$,

$\vec{F}_{horiz} = \phi([S_{horiz}(1), \ldots S_{horiz}(n)])$,

#### 2.3.3 Shape Analysis: Vertical Axis

Here the distinction is between *Rise* and *Sink* on the vertical axis. This distinction was quantified by measuring the average distance on axis y of each joint from the CM. This quantification is based on the assumption that the body is "longer" when rising.

$S_{vert}(t) = \sum_{j \in Joints} \left| \vec{P}_j - \vec{P}_{CM} \right|,$

$\vec{F}_{vert} = \phi([S_{vert}(1), \ldots S_{vert}(n)]),$

#### 2.3.4 LMA Effort Analysis: Time Category

Here the distinction is between *Sudden* and *Sustained*. This quality was quantified by the skew of the acceleration, relying on the assumption that the acceleration of a sudden movement will be skewed further to the left, i.e., will get a higher value at the beginning of the movement.

#### 2.3.5 Effort Analysis: Space Category

Here the distinction is between *direct* and *Indirect* motion. This quality was quantified by the angle between the movement vector of a joint to the next one, relying on the assumption that in direct movement every vector will be in the same direction as the last (the angle between them is small). The velocity direction $V$ is calculated by $\vec{V}_j(t) = \vec{P}_j(t+1) - \vec{P}_j(t)$, and the angles between a direction to the next one is calculated with the inner product $\vec{A}_j(t) = \vec{V}_j(t+1) \cdot \vec{V}_j(t)$.

### 2.4 Performance Evaluation

From a statistical point of view, we have 18 possible labels (Laban qualities) for every clip. Each clip was a combination of just a few of these, often 3-4, which means that there is about an 85% chance that a quality won't appear in a clip. Due to this sparsity, accuracy alone is not a relevant metric for the performance evaluation because one can get 85% accuracy by stating that for every recording none of the qualities appear. A better evaluation would have to combine the precision and recall rates of the classifier. This can be done using the F1 score:

$$F_1 = \frac{2 \cdot precision \cdot recall}{precision + recall}.$$

### 2.5 Feature Selection

Every clip is extracted into a vector of 6120 features, most of which are noisy or redundant, thus requiring massive feature selection. The feature selection is done in three stages:

- Computing the Anova F-value for every feature over the training set. Cross-validation was used to determine the optimal number of features that should be left. As seen in Figure 5, filtering out most of the features yielded better results than not filtering them, where using the top 4% of features was optimal.

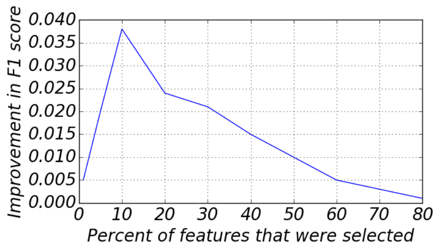


Figure 5: Influence of the number of features on the performance. The selection was made according to statistical significance. The blue line is the difference between the score with and without feature selection. It can be seen that the optimal fraction of features to select is 4%.

- The second phase of feature selection was conducted by Information Gain (IG) rating of the features. As seen in Figure 6, the optimal ratio was obtained by selecting the top 60% out of the features that remained after the first phase of feature selection. Examples of qualities and their most significant feature are given in Table 1. The "Information Gain" metric used in the table is defined as:

$$IG(T, f) = H(T) - H(T|f),$$

  where T is the training set, f is a feature, and H() is the information entropy of a dataset.

- The third phase of feature section was conducted using the Least Absolute Shrinkage and Selection Operator (LASSO) regularization.

| Quality | Feature Description | Information Gain | p-value |
|---|---|---|---|
| Jump | Vertical relative position of center of mass | 0.28 | 3.00E-50 |
| Spread | Horizontal relative position of left elbow | 0.25 | 2.20E-49 |
| Rotation | Left shoulder horizontal acceleration | 0.21 | 4.80E-46 |
| Up+Rise | Vertical relative position of left elbow | 0.2 | 3.00E-31 |
| Free+Light | Left elbow angle's variability | 0.16 | 1.10E-24 |
| Rhythmicity | Vertical relative position of center of mass | 0.16 | 1.50E-11 |

Table 1: Example of several qualities and the feature found to be the most informative for them. "Relative position" stands for the position of the joint relative to the ancestor joint in the joint hierarchy.

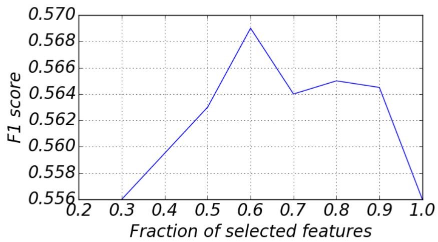


Figure 6: Influence of the number of features selected with IG from the subset of features chosen in the first phase on the performance. The optimal ratio was 60%.

# 3 Experimental Setups and Results

## 3.1 Multilabel Classification

Multilabel learning deals with the problem where each instance is associated with multiple labels simultaneously, where the number of labels is not fixed from instance to instance. The task of this learning paradigm is to predict the label (Laban quality) set for each unseen instance (skeletal recording), by analyzing training instances with known label sets. The multilabel approach taken in this paper is to break the LMA problem into 18 binary classification tasks — one for every Laban quality — where every binary decision is whether or not the quality exists.
The following subsections will describe several experimental setups where the results in each will serve as a baseline for the next.

## 3.2 Per CMA Evaluation

In this experiment the train and test datasets are taken from the same CMA. The performance on every Laban quality separately is demonstrated on a dataset of one of the CMAs in Figure 8. In Figure 7 the incremental evolution of the algorithm is described from step to step with the next notation:

- *Chance* stands for randomly tossing a balanced coin in every classification decision.
- *NN* stands for applying the Nearest Neighbors algorithm.
- *LinearSVC* stands for Support Vector Classifier (SVC) with a linear kernel.
- *LabelBalancing* stands for giving greater weight to clips that contain the quality due to the small fraction of them in the whole dataset.
- *Lasso*, *SFS* (Statistical Feature Selection), and *InfoGain* (information gain based feature selection) were described in the *Feature Selection* section.

## 3.3 Mixed Dataset Evaluation

In this section the datasets of all of the CMAs were mixed. In the learning and testing process the origin (CMA) of the instance was ignored.

### 3.3.1 Single Task Learning as a Baseline

As a baseline we applied the SVC based flow that was described in the last section on the mixed dataset. The results are shown in Figure 9. It can be seen that the performance improves in comparison to the per CMA evaluation of the last section. There are two reasons for this improvement, the first is the increase in the dataset's size when merging a

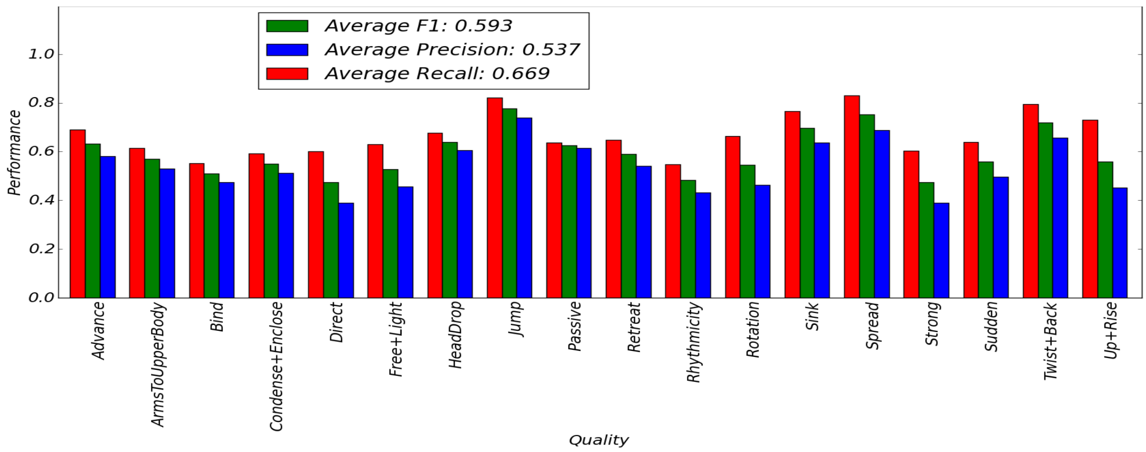


Figure 8: Recall, precision and F1 score of each Laban quality separately. The evaluation was conducted on a dataset that was captured on only one CMA.

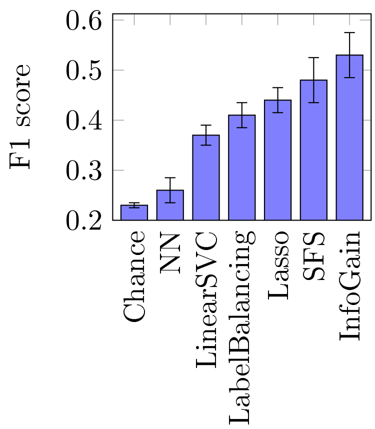


Figure 7: Evaluation of every CMA's dataset separately in the single task learning setting. Each column represents an additional step in the algorithm's evolution. The results are the average F1 score and its standard deviation (STD) between the CMAs.

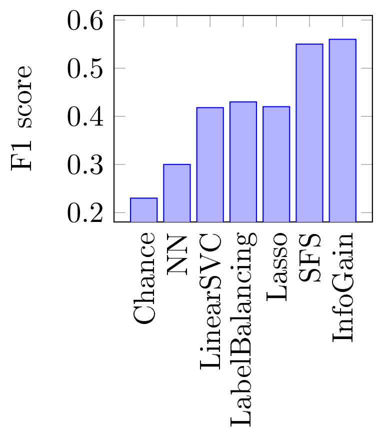


Figure 9: Evaluation on CMA mixture dataset in single task learning setting. Every Column is an additional step in the algorithm's evolution.

few CMA datasets together, and the second is diversity of the clips, which improves the model's generalization ability.

#### 3.3.2 Multitask vs Single Task Learning

We found that multitask learning for all the 18 qualities together exhibited superior performance to learning a classifier for each problem separately. For the multitask setting we used Multitask Elastic Net (MEN) regularization, which is the multitask regularization method of Zou et al. [15], where the optimization objective is:

$$\|Y - XW\|_F^2 + \lambda_1 \cdot \|W\|_{2,1} + \lambda_2 \cdot \|W\|_F^2, \quad (1)$$

$\lambda_1$, and $\lambda_2$ are hyper-parameters, where,

$$\|W\|_{2,1} = \sum_i \sqrt{\sum_j w_{ij}^2},$$

i.e., the sum of norm of each row (also known as mixed norm), and

$$\|W\|_F^2 = \sum_i \sum_j w_{ij}^2,$$

i.e., the Frobenius norm. Feature selection was carried out by averaging the statistical significance of each feature with respect to all of the tasks (this is in contrast to the single task learning flow, where every task had its own feature selection). As seen in Table 2, the multitask setting improved the F score by 7%, indicating that the tasks are correlated and more might be learned from the small dataset when using this setting.

| Metric | Single task | Multitask |
|---|---|---|
| Precision | 0.46 | **0.59** |
| Recall | **0.71** | 0.65 |
| F1 | 0.56 | **0.6** |

Table 2: Multitask vs Single task learning performance evaluation on a CMA mixture dataset.

#### 3.3.3 Performance of Every Quality in Multitask Setting

The performance over every quality as classified by the MEN in Table 3. During the MEN optimization (1), the mixed norm term $\|W\|_{2,1}$ promotes sparsity in the weights matrix $W$ such that for every row in the matrix, if one coordinate is equal to zero, then every coordinate in the row will be equal to zero.
The generalization ability of the model was enhanced by the fact that the decision which features to select is influenced by all the qualities, (feature $f_i$ is selected in the MEN if the row $r_i$ in $W$ is not all zeros). The most significant improvement were in the qualities that performed worse in the single task learning setting (*Strong* and *Sudden* for example).

| Quality | Precision | Recall | F1 score |
|---|---|---|---|
| Jump | 0.89 | 0.81 | 0.85 |
| Twist and Back | 0.69 | 0.85 | 0.76 |
| Sink | 0.62 | 0.79 | 0.69 |
| Rhythmicity | 0.59 | 0.72 | 0.65 |
| Spread | 0.55 | 0.76 | 0.64 |
| Head drop | 0.60 | 0.66 | 0.63 |
| Rotation | 0.66 | 0.60 | 0.63 |
| Free and Light | 0.45 | 0.94 | 0.61 |
| Up and Rise | 0.67 | 0.54 | 0.60 |
| Condense and Enclose | 0.44 | 0.84 | 0.58 |
| Arms To Upper Body | 0.67 | 0.54 | 0.60 |
| Advance | 1.00 | 0.38 | 0.55 |
| Retreat | 0.50 | 0.59 | 0.54 |
| Passive | 0.40 | 0.85 | 0.54 |
| Bind | 0.44 | 0.61 | 0.51 |
| Direct | 0.56 | 0.49 | 0.52 |
| Sudden | 0.61 | 0.41 | 0.49 |
| Strong | 0.29 | 0.42 | 0.34 |
| **Average** | **0.59** | **0.65** | **0.60** |
| **SD** | **0.17** | **0.17** | **0.11** |

Table 3: Recall, precision and F1 score of each Laban quality on a CMA mixture dataset. The learning was done in a multitask setting. The number of features that weren't nullified by the mixed norm regularization is 282 (same features for all of the tasks). The F1 average and standard deviation over the qualities is shown in the last row of the table.

### 3.4 Evaluation on an Unseen CMA

In this experiment the test set was taken from a CMA who did not appear in the train set. As shown in Figure 10, performance degrades on the unseen CMA from 0.6 to 0.57. We blame the degradation on the large variability between clips from one CMA to another. Every CMA performed different gestures, in different postures (some sitting and some standing) and in different contexts (some were dancing while some were acting).

### 3.5 Validation on Ordinary People

The final validation was conducted on ordinary people (non-CMAs). We designed several daily actions (greeting friends or playing with a balloon, for example) and the CMA committee tagged the clips. This dataset was small, with a focus on the qualities that we found easier to recognize. The evaluation is shown in Figure 11.

## 4 Conclusion

We developed a method for recognizing Laban qualities using the Microsoft Kinect sensor. Our method obtained a recall and precision of about 60% over the qualities. The larger movements, such as *jump*, *spread*, and *sink*, are easier to quantify, and hence easier to recognize (precision and recall of 60-90%). The more subtle qualities, such

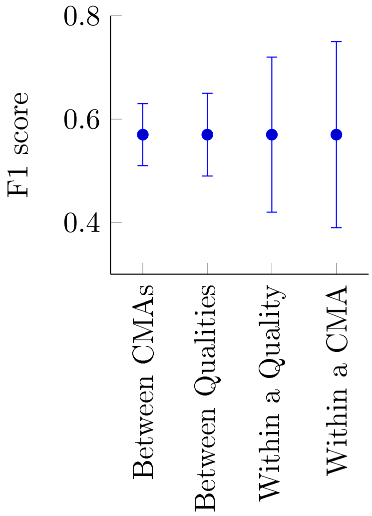


Figure 10: Confidence intervals of F1 score in quality detection of an unseen CMA. Every confidence interval is two standard deviations (STD) long. In every trial one CMA was the test set, while the classifier was trained on the rest. The mean F1 score is 0.57. The measures from left to right are: STD between CMAs when every CMA's score is an average the scores of his or her qualities; STD between qualities when every quality's score is an average of all of the CMAs' scores for this quality; an average of qualities' STDs, where every STD is between CMAs within a quality; an average of CMAs' STDs, where every STD is between qualities within a CMA's dataset.

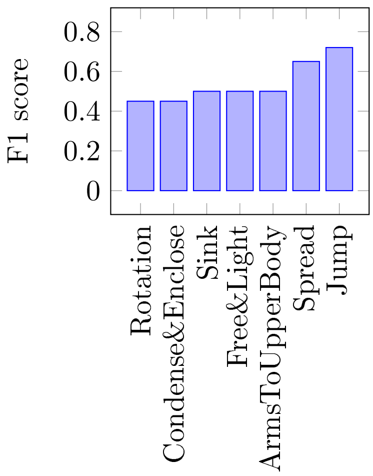


Figure 11: Performance on ordinary people (non-CMAs) instructed to perform several tasks.

as *strong* and *passive*, are harder for us to quantify in kinematic measurements, which causes a degradation in the performance (precision and recall of 40-60%).

The improvement of the F1 score from a single task learning setting (0.56) to a multitask setting (0.6) demonstrates the synergy of a shared model for several correlated tasks. The mild degradation of the F1 score from a seen CMA (0.6) to an unseen (0.57) shows a very good generalization ability of our linear classification model. This ability derives from our focus on the MEN regularization terms, which resulted in our model being not too rich, even sparse, and thus not over-fitted.

Overall we believe that we succeeded in capturing the essence of most of the qualities, using a cheap ($100) and widely available sensor. We believe that our work will provide the foundation and inspiration that will make the LMA method applicable in many more methodologies and processes.

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